Essays on Global Firms

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Abstract

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The field of International Trade aims to study the consequences of the spatial disconnection between the activities of production and consumption, which has been allowed by the increasing opening of the economies. However, while most of the history of the field has focused on the role played by production in shaping trade patterns, only recently researchers have emphasized the importance of demand characteristics. This dissertation follows these recent works by containing three essays that specifically study the importance of demand characteristics on export patterns at the microeconomic level.

In the first chapter of this dissertation, I explore the importance of the dynamic aspects of demand on the export decisions made by firms. Standard dynamic models of trade identify sunk entry costs as the main export barrier faced by firms. However, these large entry costs are inconsistent with the existence of many small new exporters with low survival rates in foreign markets. In this chapter, I study the role of destination-specific demand dynamics by introducing, in a dynamic model of trade, the idea that firms gradually accumulate consumers in foreign markets. Estimating the model using export data from individual French firms, I show that this consumer margin is consistent with the dynamics of sales, prices and survival of exporters, but also leads to much lower estimates of the entry costs of exporting - about one third of those estimated in the standard model. Moreover, this change in the nature of trade barriers has important implications at the aggregate level. In contrast to the standard model, this model correctly replicates the slow response of trade to shocks and the increasing contribution of the extensive margin in this response. Finally, I demonstrate using out-of-sample predictions that the model better predicts actual trade responses to an observed shock than the standard model.

The second chapter presents a novel instrumental variable strategy to estimate product quality at the micro level using trade data. Written with Gabriel Smagghue from University Carlos

III of Madrid, this work develops a new firm-specific instrument, based on variations in exchange rates combined with firm-specific import shares, that delivers, under weak assumptions, consistent estimates of demand elasticity and firm product quality. Implementing our method using French customs data, we document the reliability of these measures through correlations with firm characteristics and alternative measures of quality. Finally, we use our estimates to document the quality response of French firms when facing low-wage competition on foreign markets.

Finally, in the third chapter of this dissertation, I document the positive correlation between the size of a firm and its advertising intensity - measured by the amount spent in advertising as percentages of sales. Taking advantage of firm-level information about advertising expenditures from the Chilean manufacturing census, I show that this correlation holds between firms operating within a similar industry, and is stronger in industries with a larger scope for vertical differentiation. Building on these findings, I develop a model of advertising with heterogeneous firms, based on Arkolakis (2010). In addition to using advertising to inform consumers about the existence of their good, firms can use advertising to affect consumers' valuation of their products. Consistent with the empirical findings, this latter feature of advertising leads to a positive link between the advertising intensity of a firm and its size. Moreover, this link is amplified by a parameter describing the degree of vertical differentiation of the product.

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Chapter 1

An empirical dynamic model of trade with consumer accumulation

Paul Piveteau[1]

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1.1 Introduction

The decision by individual firms to enter into an export market is responsible for most of the variations in aggregate trade flow across destinations and time. For instance, Bernard et al. (2007) estimate that around 80 percent of the decline of international trade with geographical distance is due to a reduction in the number of exporting firms (extensive margin) rather than changes in exports within the firm (intensive margin). Therefore, understanding the determinants of export decisions and the barriers that firms face in foreign markets is critical.

Standard dynamic models of trade that quantify the nature of these trade costs, such as Das, Roberts, and Tybout (2007), highlight the prevalence of large sunk entry costs as barriers to trade. These large entry costs are necessary to explain the persistence in export decisions, the so-called hysteresis of exporters. However, the prevalence of these entry costs is incompatible with important characteristics of new exporters' dynamics that have been recently documented in the literature: most new exporters start small and only a small fraction survives and expands in these foreign markets.

This paper introduces inertia in consumers' choices into a dynamic empirical model of trade to reconcile the observed hysteresis in exporting decisions and the dynamic features of new exporters. I introduce this inertia through the existence of a stock of consumers that firms accumulate throughout their experience in foreign markets. To assess the importance of this accumulation of consumers on exporters' dynamics, I develop a Markov Chain Monte Carlo (MCMC) estimator that allows me to include other sources of persistent heterogeneity at the firm level such as productivity and product appeal, and estimate the model using export data from individual French firms. The estimated model correctly predicts lower survival rates for new exporters, but also estimates low sunk entry costs of exporting - on average, entry costs are about one third of those estimated in a model without consumer accumulation. These results have important implications regarding the aggregate predictions of the model: aggregate trade responds slowly to shocks and the contribution of the extensive margin is larger in the long run than the short run. Both of these patterns have been recently documented in the literature; however, they are inconsistent with the standard model.

I start by presenting three stylized facts about exporters that highlight the importance of growth in demand in these exporters' dynamics. Consistent with recent studies, sales and survival rates of young exporters are low upon entry, but grow at a fast rate during the first years of exporting. Moreover, this growth is not due to variations in prices during the life of an exporter, but instead, prices tend to also increase on average with export experience. This result suggests that the growth in sales observed in the years following entry into a foreign market is mainly driven by an increase in the demand shifts received by exporters.[2]

Based on these findings, I develop an empirical dynamic model of trade in which consumers only buy from a limited set of firms, which generates inertia in their consumption choice.[3] Therefore, each firm will have a different stock of consumers, depending on its history in the foreign market; this will shape its profit, expectations, and decisions in each market. This addition to the model has two important consequences on the dynamics of exporters: first, it implies that new exporters will start with low levels of sales and profits when entering a new destination. As they survive and accumulate consumers, their sales and profits will increase, inducing increasing survival rates with their experience in a destination. Second, because current sales are a source of customer acquisition, firms have incentives to reduce their price to foster the accumulation of new consumers.[4]

In order to study the importance of this mechanism on exporters dynamics, I structurally estimate this model using customs data from France. I perform this estimation on the wine industry, which has the double advantage of being an important exporting industry in France, while also being composed of single-good producers. The dataset provides sales and quantities exported by individual firms on each destination market, which allows me to account for several sources of persistent heterogeneity across firms and destinations. In addition to heterogeneity in demand across destinations, the model identifies three types of heterogeneity at the firm-level: product appeal, defined as a demand shifter that is common across destinations;[5] productivity, acting as a cost shifter; and the firm's consumer base, which is identified from within-firm demand variations across destinations. Because this large number of persistent unobservables complicates the estimation of

[2] This finding is consistent with recent papers that show the importance of demand characteristics as source firm heterogeneity (Hottman, Redding, and Weinstein, 2016; Roberts, Xu, Fan, and Zhang, 2012).

[3] This extends to a dynamic setting the consumer margin first introduced in international trade by Arkolakis (2010). This inertia could be alternatively modeled with habits formation or other sources of state-dependence in demand.

[4] Recent empirical evidence for this type of mechanism on domestic market was found by Foster et al. (2016) who studied the behavior of new firms producing homogeneous goods.

[5] Khandelwal (2010) at the product level or Hottman, Redding, and Weinstein (2016) at the micro level, also define appeal or quality as the demand shifter after controlling for prices in a demand equation. However, I assume that appeal does not vary across destinations.

the model, I employ a Markov Chain Monte Carlo (MCMC) estimator that will account for this unobserved heterogeneity, and facilitates the solution of the dynamic problem of the firm. Therefore, this estimator will allow me to obtain value estimates of the entry and per-period fixed costs of exporting, which will be identified by rationalizing the actual entry and exit patterns of exporters on the different export markets.

The results of the estimation demonstrate the importance of the accumulation of consumers to replicate exporters' dynamics. The introduction of state dependence in demand improves the ability of the model to fit the dynamics of young exporters: the model can rationalize lower survival rates for young exporters, as well as the growth of sales and survival as exporters become more experienced. Moreover, estimated entry costs of exporting are small relative to existing estimates. The average cost to start exporting to a foreign European destination for a wine exporters is around 33 000 euros, around 78 percent of the average revenue in these destinations.[6] Because the accumulation of consumers accounts for an important part of the dependence in export decisions, large entry costs become unnecessary to rationalize the hysteresis in export markets. To confirm this finding, I estimate a version of the model without consumer accumulation and obtain an estimate of the average entry cost to European destinations of 98 000 euros, roughly three times the estimates of the full model.

These results have important implications at the aggregate level. In particular, the model will generate aggregate adjustments in response to trade shocks that are consistent with patterns documented in the literature. First, the model predicts a slow increase in trade as a response to a permanent positive trade shock: because of the slow accumulation of consumers, it takes time for existing and new exporters to expand and reach their new optimal stock of consumers. As a consequence of these adjustment frictions, the trade response will be larger in the long-run than the short-run. In my simulations, the ratio between the long and the short-run elasticities is around three, a value that is consistent with the ratio of elasticities used in the international trade and international macroeconomics literature. Second, the model can predict the increasing contribution of the extensive margin during a trade expansion. Recent papers, Kehoe and Ruhl (2013) and Alessandria et al. (2013) in particular, document how the extensive margin tends to have a small contribution in the short-run but plays a significant role in the long run in explaining trade

[6] Or equivalently 2.7 times the median yearly revenue on these destinations.

growth. The model with consumer accumulation generates a relative contribution of the extensive margin two to three times larger in the long-run than in the short-run. Because the technology for accumulating consumers displays decreasing returns, new exporters will record larger growth than established exporters in the years following the shock, hence increasing their contribution to trade relative to older exporters throughout these years.

Finally, I employ out-of-sample predictions to further confirm the importance of this consumer accumulation in explaining firms' response to shocks. During the sample period, large variations in exchange rates led to a decrease of the exported values and market shares of French wine on the Brazilian market.[7] Based on these variations in exchange rates that affected the relative price of French wine, I construct variations in aggregate demand for French wine from Brazilian consumers. This aggregate demand, in conjunction with outcomes from the model estimated on other destinations, allows me to generate predictions on entry, sales and prices in the Brazilian market, and compare them to the actual realizations of these variables. The model with consumer accumulation is able to replicate, unlike the standard model, the decrease in total trade and in the number of exporters. The decrease in estimated entry costs between the two models, reduces the option value of exporting. Therefore, as economic conditions fluctuate, the model with consumer accumulation (and low entry costs) will predict larger inflows and outflows of exporting firms, and therefore larger variations in total trade.

This paper is closely related to the literature investigating exporters and firms dynamics. Das, Roberts, and Tybout (2007) is the first study to quantify entry and per-period fixed costs of exporting by estimating an entry model of trade. Their estimation emphasizes the importance of entry sunk costs to explain the hysteresis of export decisions.[8] My paper builds on their contribution by capturing this hysteresis through state dependence in demand rather than sunk entry costs, and demonstrating the importance of this extension for a number of micro and macro-level facts. Many recent studies have documented and studied the specific dynamics of new exporters. Nguyen (2012), Albornoz et al. (2012), Berman et al. (2015) and Timoshenko (2015) emphasize the role of demand uncertainty and experimentations to explain exporters dynamics, while Rauch and Watson (2003)

[7]The Brazilian devaluation in 1999 and the depreciation of the Argentinian peso in 2002, that fostered Argentina exports to Brazil, have increased the relative price of French wines.

[8]Lincoln and McCallum (2015) similarly shows the prevalence of entry costs when estimating fixed costs of exporting for US firms.

and Aeberhardt et al. (2014) develop models where exporters need to match with foreign customers in order to trade. Foster et al. (2016) and Fitzgerald et al. (2016) introduce consumer accumulation to explain the post-entry growth of firms in domestic and foreign markets respectively.[9] However, they do not study the participation decision in these markets. Similar to my paper, Eaton et al. (2014) also develop an entry model with accumulation of customers: they use an importer-exporter matched dataset to estimate an empirical model in which exporters grow through the search of foreign distributors and the learning of their own ability.[10] However, while they do not allow for other margins of firms' growth on foreign markets, my model will feature other sources of time-varying heterogeneity at the firm level, such as productivity and product appeal. Therefore, I am able to investigate the importance of this new margin on exporters' dynamics, and its consequences on the estimation of trade costs and the predictions of aggregate trade movements.

This article is also related to macroeconomic papers that similarly introduce a consumer margin, or study aggregate trade dynamics. Arkolakis (2010, 2016) develops a static framework in which a consumer margin at the firm level generates convex costs of participation to foreign markets and heterogeneous elasticities of trade in the cross section of firms. I extend this consumer margin to a dynamic setting to empirically investigate its consequences on exporters' dynamics. Drozd and Nosal (2012) and Gourio and Rudanko (2014) show how convex adjustment costs of market shares can explain several puzzles in international macroeconomics and adjustments of important variables along the business cycle. Moreover, several recent papers have investigated the reasons for the slow response to trade, and the discrepancy between short and long-run elasticities of trade.[11] This series of papers develops macroeconomics models to explain this discrepancy between elasticities through the role of entry and exit of firms, the importance of establishment heterogeneity or the existence of export-specific investment (Alessandria and Choi, 2007, 2014; Alessandria, Choi, and Ruhl, 2014). My paper also explains this discrepancy by combining the role of consumer accumulation at the firm-level, and the entry of new exporters. However, whereas I do not develop a calibrated general equilibrium model, I estimate an entry model using micro-data to discipline the role of this mechanism and investigate its consequences on aggregate trade dynamics.

[9]See also Rodrigue and Tan (2015) that describes demand-side explanations to understand exporters dynamics.

[10]See also Akhmetova and Mitaritonna (2012) and Li (2014) that show the importance of demand uncertainty, and Aw et al. (2011) looking at the impact of R&D activities on exporter decisions.

[11]See Ruhl (2008) for a review on the discrepancy between trade elasticities in the international macro and international trade literature.

Finally, this study heavily builds on the literature related to the estimation of dynamic discrete choice models (DDCM). These models display a high level of nonlinearity and therefore require the development of specific techniques to facilitate their estimation. Rust (1987) and Hotz and Miller (1993) can be cited as seminal papers in the development of these techniques. More specifically, I employ a MCMC estimator recently developed by Imai et al. (2009) and Norets (2009), that allows me to account for the existence of persistent unobservables, as well as solve the full solution of the DDCM.[12]

The outline of the paper is the following: in the next section, I will present stylized facts about the trajectories of exporters, that will emphasize the importance of demand in exporters' dynamics. In section 1.3, I build an empirical model of export entry that is consistent with these facts. I present the estimation method in section 1.4, and show the results of the estimation on a set of French wine makers in 1.5. Finally, section 1.6 will inspect the aggregate implications of the estimated results through simulations and out-of-sample predictions, and section 1.7 will conclude.

1.2 Stylized facts about exporters dynamics

In this section, I present three important facts about exporters' dynamics using French customs data. First, new exporters have low survival rates upon entry, but survival increases quickly with experience. Second, exported values grow with age in foreign markets, even after controlling for survival. Third, prices also increase with exporters' age.

These facts are consistent with the empirical model I will present in the next section: first, the high level of attrition across age will require the model to account for endogenous selection. Moreover, the rise in sales, while prices increase on average, indicates that this growth is driven by a positive shift in the demand schedule of the firm: the consumer margin introduced in the model will be able to replicate this increase as exporters will start small, and will accumulate consumers with experience. Finally, the low mark-up charged by young firms to foster this accumulation will explain the observed increase in prices with age.

[12] An application of this estimation method in Industrial Organization can be found in Osborne (2011).

1.2.1 Data

The dataset I used in this paper is provided by the French customs services. These data record yearly values and quantities exported by French firms from 1995 to 2010.[13] Yearly trade flows are disaggregated at the firm, country and eight-digit product category of the combined nomenclature (CN). This dataset will be used to present stylized facts about new exporters in this section, and a restricted sample from the wine industry will be used to conduct the structural estimation described in the next sections.

I perform a number of procedures to improve the reliability of the data. In particular, I correct for the existence of a partial-year bias, and improve the reliability of the unit values. The partial-year bias comes from the mismatch between calendar years and exporting years: because trade data are based on calendar years, the first year of activity of a new exporter will report lower sales on average, since this exporter potentially entered anytime during that year.[14] These partial years will imply an overestimation of the growth rate between the first and second year of export. To correct for this bias, I readjust the dataset using information available at the monthly level. For each new entry by a firm on a new destination, I readjust the month of entry, and adjust accordingly the dates of the subsequent exporting flows for that firm. Aggregating this adjusted dataset at the yearly level, I obtained a transformed dataset that does not display this bias. Second, in order to improve the reliability of the unit values, I drop all the product categories that use weight as unit of measure. Even though the weight of a product is sometimes the relevant unit for that product, it appears that it is used as unit when the type of product in a category is not homogeneous, and therefore casts some doubt on the use of these quantities to create unit values.[15] In addition to these two important adjustments, Appendix A.1 describes additional procedures implemented on the dataset to improve its reliability.

Table 1.1 provides some information on the distributions of the number of observations along different dimensions. Similarly to what have been documented in the literature, trade flows from

[13]This dataset records most of the exporting and importing flows of Metropolitan French firms: there exists thresholds under which a firm does not need to report its exporting activity (In 2001 these thresholds were 1,000 euros for exports to countries outside of the European union, and 100,000 for the total trade within the EU.)

[14]See Berthou and Vicard (2015) and Bernard, Massari, Reyes, and Taglioni (2014) for papers investigating the extent and consequences of this bias.

[15]The main patterns displayed in the next subsection, in particular the one related to prices, appears to hold when using the products that use weights as units.

France are sparse across firms and destinations. This is true for firms across destinations or product categories in a given year, since the median exporting firm records two flows per year, usually concentrated within one product category or one destination. But this sparsity also appears across time as shown in the second panel of Table 1.1: contrary to the idea that exporting is a long-lasting activity, we can see that the median exporting spell lasts one year.[16] This is true even when exports are aggregated across product categories and exporting flows defined at the firm-destination level.

TABLE 1.1: Description of the data

Statistics	mean	p5	p25	p50	p75	p95	N
# observations							
by firm-year	8.49	1	1	2	5	28	671 403
by firm-CN8-year	2.21	1	1	1	2	8	2 581 098
by firm-dest-year	2.60	1	1	1	2	8	2 189 506
Exporting spells duration (years)							
firm-dest-CN8 level	1.67	1	1	1	2	5	3 413 456
firm-dest level	2.01	1	1	1	2	7	1 091 995

Notes: CN8 denotes an eight-digit category from the Combined nomenclature, after normalization following Pierce and Schott (2012). An exporting spell is defined as a set of consecutive yearly exporting flows.

These statistics provide an overview of the prevalence of short and frequent export flows in the the export data. In order to further investigate this aspect and understand the evolution of the other characteristics of these exporting flows, I specifically look at their trajectories across ages in the next subsections.

1.2.2 Specifications

To describe the trajectories of exporters upon entry, I look at the variation of their survival rates, sales and prices across different ages on foreign markets. I define the age of a firm-product-destination triplet as the number of years this firm has been successively exporting this product category to a market, a market being defined as a 8-digit product category-country pair. I regress the variables of interest (dummy for survival, logarithm of sales or prices) on a full set of age dummies.

[16] An exporting spell is defined as a set of consecutive yearly exporting flows between a domestic firm and a foreign destination, or a 8-digit product category - firm pair and a foreign destination.

The specification will be augmented with fixed effects that will control for the large heterogeneity that exists across industries, destinations and years. Formally, indexing a firm by f, a destination by d, a product category by p, and a year by t, the econometric specifications are the following:

$$Y_{fpdt} = \sum_{\tau=1}^{10} \delta_\tau \mathbb{1}(\text{age}_{fpdt} = \tau) + \mu_{pdt} + \varepsilon_{fdt}, \tag{1.1}$$

where age_{fpdt} is defined as the number of consecutive years a firm f has been selling the good p to destination d. Y_{fpdt} will be the logarithm of export sales, the logarithm of prices (unit values),[17] or a dummy equal to one if the firm is still exporting to the market the following year. μ_{pdt} will be a market×year-specific fixed effect such that the variations that identify the coefficients δ_τ comes from variations across firms of different ages, within a given destination×product category×year pair.

Trade data at the firm-product level are known to have a very large level of attrition. These low levels of survival, especially in the early years of exporting, imply that firms surviving 10 years differ substantially from firms who recently started to export. Consequently, the variations that the regressions will capture when comparing old and new firms will mostly come from a selection effect comparing different set of firms, rather than changes across ages for a given set of firms. In order to partially account for this dynamic selection, I also present the results when only looking at firm-product-destination triplets that survive 10 years in their specific markets. Even though this only partially accounts for selection, since surviving firms are also firms with specific trajectories, it will show that the observed relationships are not only due to dynamic selection, but also appear within a constant set of firms.

Another possibility to partially account for this dynamic selection would be to use firm-product fixed effects, or first difference transformations. These transformations would control for the heterogeneity across firms, and only capture variation within a firm-product-destination triplet across ages. However, the identification of a trend with age is not possible using variations within a given triplet because the increase of age is a treatment that applies to all firms, and therefore cannot be separately identified from a cohort effect. I discuss related specifications at the end of the section.

[17] I use the terms unit values and prices interchangeably throughout the paper. As usual with this type of dataset, prices are obtained by dividing export values by export quantities.

1.2.3 Results

Here I present three important facts about exporters, namely the growths of the survival rates, exported values, and prices with export experience on foreign markets. Regarding the growth of sales and survival rates, these facts have been extensively documented and discussed in the literature in international trade and macroeconomics.[18] However, I show that these facts still hold after controlling for the partial-year bias highlighted by Berthou and Vicard (2015) and Bernard, Massari, Reyes, and Taglioni (2014). Moreover, the increase of prices has not been documented, to my knowledge, using a comprehensive trade dataset, even though Foster, Haltiwanger, and Syverson (2016) documents similar patterns for the domestic prices of homogeneous goods, and Macchiavello (2010) show evidence of similar trajectories for prices of Chilean wine in the UK market.[19]

Fact 1: Survival rates are low for new exporters, and strongly increase with their age First of all, the probability to survive on a market, i.e. to export on this market the following year, is very low for the average exporter. Figure 1.1 displays the average survival rate for a firm-product pair on a foreign market, for different age or experience levels. For an exporter in its first year, the probability to export the following year is roughly 35 percent. However, this survival probability rapidly increases once exporters have survived several years: this rate is larger than 50 percent at age 2, and close to 75 percent at age 6. This result reflects the same idea highlighted in the previous section that most export spells are short lived.

These low, yet increasing, survival rates will have theoretical and methodological consequences. On the theoretical side, it will be important to have a model of export entry that can replicate and explain these low survival rates: a model in which entry costs are prevalent will have difficulties explaining why so many firms exit the export market so rapidly. On the methodological side, these very low survival rates imply it will be necessary to account for this large attrition when interpreting differences across firms in a reduced form exercise, and to model this entry decision in the design of the structural model.

[18] See for instance Ruhl and Willis (2008) for a presentation of these facts and the associated puzzles.

[19] See also Eizenberg and Salvo (2015) which shows evidence of prices cut in the Soda Brazilian market that are motivated by consumers' inertia in consumption.

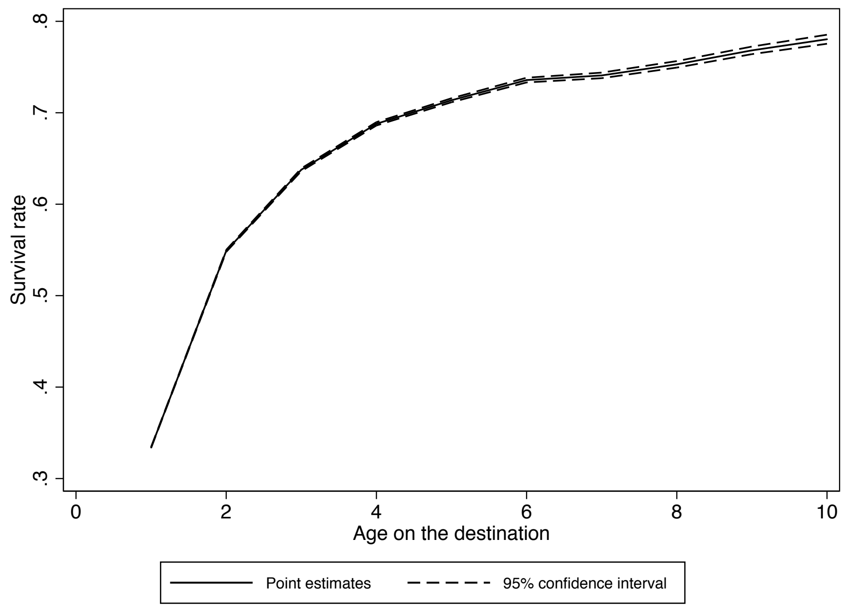

FIGURE 1.1: Survival rates across export ages

Notes: The figure reports the average survival rate of a firm-product category pair on a destination at different ages. The estimates are obtained from the regression (1.1) that uses as dependent variable a dummy equal to one when the firm-product pair exports to the destination the following year, and includes product category×destination×year fixed effects. The age on a destination is defined as the number of years a firm-product pair has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors estimates clustered at the firm-product-destination level.

Fact 2: Exported values increase with firm age in a destination, even more so in the first years of exporting

Turning to the variation of sales across ages, Figure 1.2 documents the large growth rates of exported values across ages. This figure is obtained by plotting the results from regression (1.1), after normalizing the average log sales at age one to be zero. When comparing exported values, exporters which are in their third year of exporting will export more than twice as much compared to a new exporter. This difference reaches an order of 7 when comparing an exporter with 10 years of experience to a new exporter. However, it is important to note that these differences are mostly due to a strong selection across exporters: old exporters, who by definition managed to survive on foreign markets, were initially larger than the average new exporter. The right panel in Figure 1.2 emphasizes this point by looking at the relationship when restricting the set of exporters to those surviving 10 years. Accounting for survival, the growth rate of sales with export age is strongly reduced. Nevertheless, surviving exporters still record an average growth rate of 25 percent between ages one and two. Moreover, this growth appears to continue the first six years: at this age, exporters tend to be on average two times larger compared to their first year of exporting.

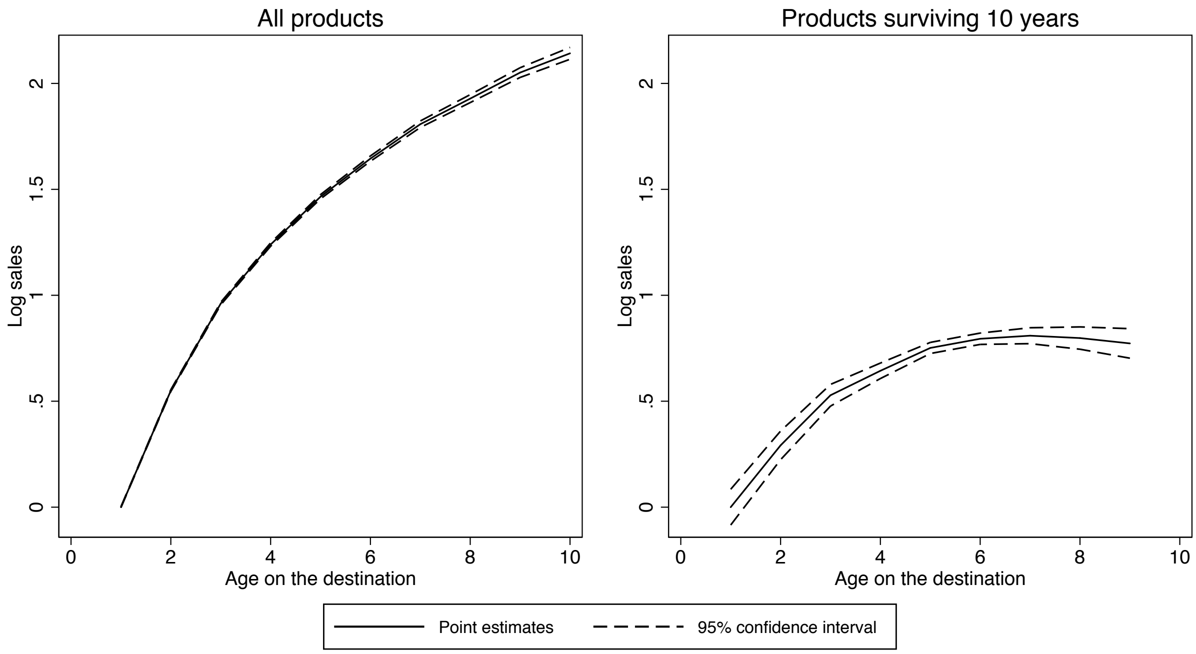

FIGURE 1.2: Sales across export ages

Notes: The figure reports the cumulative growth of sales, relative to age one, of a firm-product category pair in a destination at different ages. The estimates are obtained from the regression (1.1) that uses logarithm of sales as dependent variable, and includes product category×destination×year fixed effects. The left panel reports the results of this regression on the entire sample, while the right panel reports the result from an estimation using only the sample of firms that reach age 10. The age on a destination is defined as the number of years a firm-product pair has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors estimates clustered at the firm-product-destination level.

In conclusion, we observe substantial growth rates of sales during the first years of exports. These growth rates are large but appear to be lower than previously described in the literature because of the correction for the partial-year effect highlighted in Berthou and Vicard (2015) and Bernard, Massari, Reyes, and Taglioni (2014). Moreover, this positive relationship appears to be robust across product categories and destinations. However, it is important to emphasize that this growth could be generated by the stochastic nature of the exporting process: by focusing on surviving firms, we are looking at the “winners” of the exporting game, which could explain unusually large growth rates. Accounting for this potential mechanism will be one of the roles of the structural model introduced in the next section.

Fact 3: Export prices increase with firm age in a destination, even more so when controlling for survival.

One possible explanation for the growth in sales could be productivity improvements that lead to a reduction in the prices of the good exported, and therefore an increase in its sales. On the contrary, it appears that prices also increase with the experience of the firm on the export market.

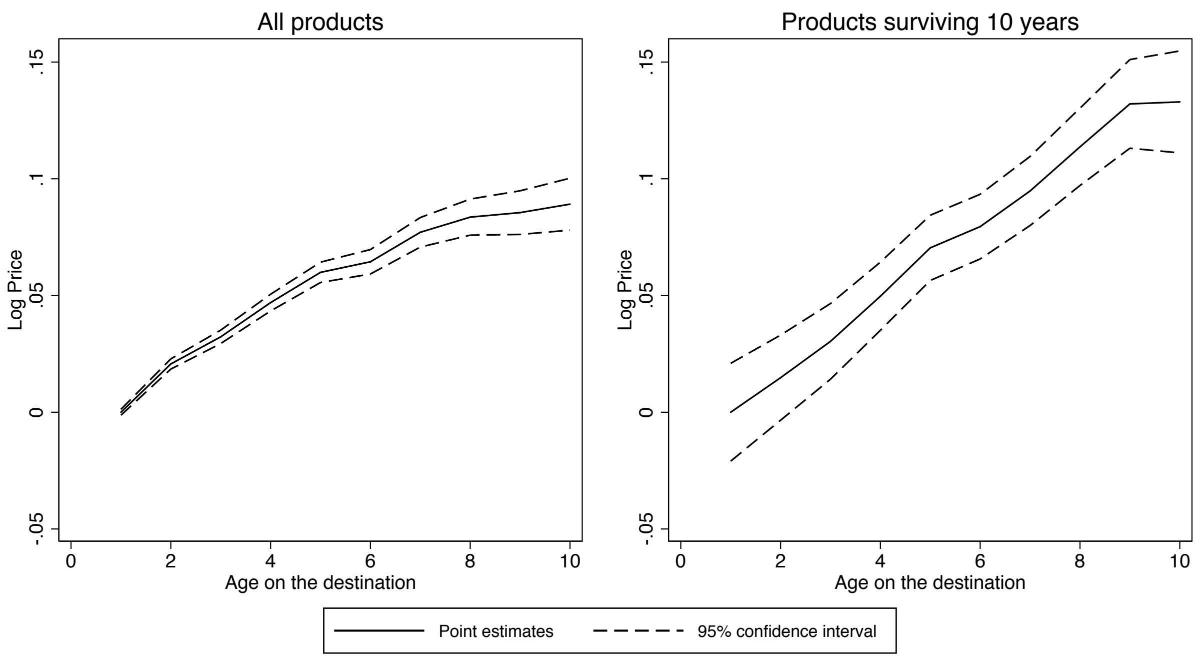

FIGURE 1.3: Prices across export ages

Notes: The figure reports the cumulative growth of prices, relative to age one, of a firm-product category pair in a destination at different ages. The estimates are obtained from the regression (1.1) that uses logarithm of unit values as dependent variable, and includes product category×destination×year fixed effects. The left panel reports the results of this regression on the entire sample, while the right panel reports the result from an estimation using only the sample of firms that reach age 10. The age on a destination is defined as the number of years a firm-product pair has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors estimates clustered at the firm-product-destination level.

Figure 1.3 reports the estimated parameters of regression (1.1) in which the average price at age one is normalized to zero. The left figure shows that the price of an exporter with 10 years of experience is on average 9 percent higher than the price of a new exporter. Similar to sales, this effect could come from a selection effect of the exporting activity: a selection process driven by the quality of the product for instance, would imply that older firms which managed to survive, have higher prices than young exporters. However, when controlling for selection by looking at surviving firms (Right panel of Figure 1.3), it appears that the growth of prices is even larger compared to the regression using the full sample: the price after 10 years appears to be in average 12 percent larger than the price charged by the same firm at age one.

Observing a larger growth of prices when looking at a constant sample of firms has two important implications. First of all, it means that costs are the main driver of the selection process: high price firms tend to disappear more in the first years such that the positive correlation between prices and age is weakened when using the full sample. Second, it implies that this positive correlation cannot be only driven by dynamic selection. Therefore, an additional mechanism is necessary to explain why firms tend to increase their price during their exporting life. The structural model presented in the following section will introduce such a mechanism, through the dynamic pricing of the firms.

There exists other methods that can partially account for the endogenous selection across ages. However, within variations cannot be used in this context as it is not possible to separately identify the role of experience, cohort and trend effects. In appendix A.2, I describe results from two specifications that use related sources of identification. The first one includes a set of firm-product-destination fixed effects, such that the identification only comes triplets that exit the market and reenter a few years later.[20] This specification documents a decreasing trend for prices and a hump shape of sales, which confirms that high price products tend to survive less on average. The second specification introduces a set of firm-product fixed effects such that the variation is obtained from the same firm-product pair which is selling to different destinations, with different ages. A potential issue with this specification comes from the endogenous sorting across destinations: older destinations are also the ones to which the firm has decided to export first. The results appear consistent with this mechanism: sales appear to grow faster with this specification, while growth in prices are smaller but still positive. Detailed results are provided in appendix A.2.

This section introduced simple facts about exporters' dynamics that will guide the empirical model developed below. We can draw three conclusions from these figures. First, survival rates are very low in export markets and grow with the age of the firm. This result has two consequences: it implies that the entry decision needs to be accounted for when studying the dynamic problem of the

[20] They are the only triplets that go 'backward' in age, and therefore are the only sources of variation.

firm. Moreover, this fact is contradictory with a world where the main barrier to export is made of sunk entry costs: in such a world, exporters would tend to keep exporting once they have overcome this important barrier. Second, sales of exporters grow rapidly in the first years of exporting. These large growth rates are also present when accounting for dynamic selection across firms. Third, this increase in sales is driven by a growth in the demand of the firm: price variations cannot explain this large increase, implying the importance of demand characteristics as main drivers of this increase in sales. On the contrary, it appears that prices tend to rise with age, even more so when controlling for dynamic selection. This pattern could be explained by a dynamic behavior of the firms that foster their growth in the early years by reducing their prices.

Despite these conclusions, it is difficult to make strong causal statements by comparing firms of different ages. This brings to light a second benefit of developing and estimating a structural model to study the entry and growth of exporters: in addition to understanding the dynamic decisions of firms, it will allow the model to control for the endogenous sorting and attrition of firms, and recover the different processes that drive the observables variables of the model. The next section introduces this model.

1.3 Structural model of export entry

This section describes an empirical model of entry into foreign markets in which the accumulation of consumers creates a new source of dependence in the dynamic problem of the firm. This model aims to identify the different sources of firms' profit in foreign markets in order to explain their export decisions. Therefore, it is crucial to allow for heterogeneity across firms and destinations, but also to allow this heterogeneity to be persistent over time. Indeed, persistent heterogeneity will be the main competing hypothesis to sunk entry costs to explain the persistence in export decisions. As a consequence, this model will feature two additional sources of persistence at the firm level - productivity and product appeal - and one persistent characteristic specific to destinations - their aggregate demand. Therefore, a potential profit for a firm-destination pair will depend on four characteristics: productivity, product appeal, aggregate demand and consumer share.[21]

[21] Therefore, I will assume that entry decisions are independent across destinations, once controlling for firms' characteristics, which will keep the state space of the dynamic problem relatively small. McCallum (2015) provides support for this assumption by finding that entry costs of exporting are mostly country specific. See also Morales et al. (2014) for a paper that use moments inequalities to maintain such a large state space.

The introduction of consumer accumulation will imply two deviations from the standard dynamic model, which will be consistent with the stylized facts presented earlier: first, firms will start small in a new market. Their sales and profit will rise in the following years as they accumulate more consumers. Second, because part of this accumulation of consumers comes from sales, firms will have dynamic incentives to lower their prices in the first years of exporting to foster their future demand.

I start by describing the demand schedule of the firm and how the accumulation of consumers affects the demand from foreign destinations. After introducing the costs associated with the production process, I solve the dynamic problem of the firm to study the consequences of this consumer margin on the entry and pricing decisions.[22] In particular, the optimal price charged by the firm will depart from a constant mark-up over marginal costs to take into account the dynamic impact of prices on consumer accumulation.

1.3.1 Demand

There exists a wide range of mechanisms that can give rise to inertia in consumption and state dependence in demand. A large literature in industrial organization has found empirical evidence of this behavior and have studied their consequences on the market equilibria and the pricing behaviors of firms. This literature also points out the large number of mechanisms that can generate this dependence in demand, as well as the difficulty to empirically disentangle these different channels. One can cite the existence of habits in consumption, the fact that searching new products is costly, or the failure of perfect information for the consumers about goods as examples of economic explanations that leads to state dependence in the demand formed by an agent (see for instance Dubé, Hitsch, and Rossi (2010) for a paper distinguishing and measuring the contribution of these different mechanisms).

In order to keep the model tractable, I will introduce state dependence in demand through the existence of a firm-specific customer base on each destination. This customer base, denoted n_{fdt}, describes the share of consumers, on a destination d at time t, that includes the product f in its consideration set. This representation follows the marketing literature that defines a consideration

[22] Note that I do not study the choices made by the firms for each product it could potentially export. Firms are seen as single-good producers in this model, and will be considered as such in the empirical application using wine producers.

set as the set of products that consumers consider when making purchase decisions.[23] It is also consistent with the idea of customer margin introduced in the macroeconomic and international trade literature.[24] This consumer base is equivalent to introducing some frictions that can explain that new exporters will start small in foreign markets and will only expand in the subsequent years. Even though I can specifically identify that these frictions are destination-specific demand frictions, one could imagine other theoretical foundations for why new exporters face little demand when they start and slowly grow in export markets.[25]

Therefore, I will assume that a new exporter has an initial share of consumer n_0 when it enters a new foreign destination. In the subsequent years, the consumer awareness of the products will be propagated through two mechanisms. First, the sales of a product will increase its awareness in the next period. Specifically, an euro increase in the sales of a product will increase by η_1 the potential share of consumers in the next period. This acquisition of consumers can arise in a situation in which consumers have imperfect information about product characteristics, and therefore use sales as a signal for the expected utility gain obtained from consuming a good.[26] Second, another source of consumer accumulation will come from word-of-mouth: I will assume that each aware consumer will share its awareness with η_2 consumers. Both of these mechanisms will generate a potential growth in the share of consumers for the firm. However, because some of these reached consumers are already aware of the existence of the product, this acquisition of new consumers will be discounted by a factor $(1-n')^\psi$ with $\psi > 0$, such that the marginal effect of sales s and consumer share n on the future share n' is

$$\begin{aligned} \frac{\partial n'}{\partial s} &= \eta_1(1-n')^\psi, \\ \frac{\partial n'}{\partial n} &= \eta_2(1-n')^\psi \end{aligned} \tag{1.2}$$

This specification is largely inspired from the marketing literature as described in Arkolakis (2010): the accumulation of consumers has decreasing returns such that it is more difficult for an established firm to accumulate more consumers relatively to a firm with a small initial share. Indeed, for

[23]See for instance Shocker et al. (1991) for an article studying the importance of consideration sets in consumers' decisions.

[24]See for instance Drozd and Nosal (2012) and Gourio and Rudanko (2014) for macroeconomic papers, and Arkolakis (2010) in international trade.

[25]For instance, one could think of a Hotelling model in which firms are uncertain about the ideal variety asked by consumers in a given market, and only comes closer to this variety as they sell and survive on this market.

[26]With CES preferences, the amount spent for a specific good is proportional to the utility gain obtained from the consumption of this good.

established firms, a significant share of these newly reached consumers will already be part of their consumer share, hence not contributing to its growth. Therefore, the parameter ψ will describe the importance of these decreasing returns, and the two parameters η_1 and η_2 will characterize the importance of the two different sources of growth in the accumulation process.

These two different margins of growth will capture different mechanisms of consumer accumulation, but more importantly will generate different optimal responses by the firm. In a world with word-of-mouth, where consumers learn from their neighbors, the growth of this consumer share could be seen as exogenous, only based on the past share of consumers. In this world, firms cannot affect this accumulation with their pricing decisions.[27] However, in a world where consumers face uncertainty regarding product characteristics and sales are seen as a signal, firms will have incentives to reduce its price in order to foster the accumulation of consumers. This distinction between these two sources of growth brings back to the distinction between structural and spurious structural dependences (Heckman, 1981), that generate different optimal responses by the firm.

Adding an initial condition to these differential equations, $n(0,0) = \underline{n}$, we obtain the following law of motion for the consumer share of a firm f, at date t and destination d:

$$n_{fdt} = 1 - \left[(1-\underline{n})^{1-\psi} - \eta_1(1-\psi)s_{fdt-1} - \eta_2(1-\psi)n_{fdt-1}\right]^{\frac{1}{1-\psi}} \tag{1.3}$$

Therefore, the share of consumers today n_{fdt} will depend on the sales s_{fdt-1} and the share of consumers n_{fdt-1} in the previous period in this market.

This share of consumer will act as a demand shifter for the firm since it will scale the amount of demand the firm will receive from each destination. To obtain the total demand of the firm, it is necessary to solve the consumption problem of the consumers. Because not all consumers know about all products, consumers will display CES preferences over a limited set of goods. Denoting Ω_i the set of goods in the consideration set of a given consumer i, the utility function is

$$U_i = \left[\int_{\omega\in\Omega_i} \exp\left(\frac{1}{\sigma}\lambda(\omega)\right)\ q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}} \qquad \sigma > 1,$$

[27] This model does not take into account advertising as a source of growth, even though this could be a natural candidate to foster consumer accumulation. The inability to observe this type of expenditures in trade datasets makes it difficult for an empirical model to account for this channel.

where $q(\omega)$ is the quantity consumed and $\lambda(\omega)$ the appeal of the product. This consumer i will maximize this utility function given a budget y_i devoted to this set of goods, and prices $\tilde{p}(\omega)$. As a solution of this optimization, the quantities $q_i(\omega)$ demanded by consumer i for a good ω are

$$q_i(\omega) = \begin{cases} \exp(\lambda(\omega))\tilde{p}(\omega)^{-\sigma}P^{\sigma-1}y_i & \text{if } \omega \in \Omega_i \\ 0 & \text{if } \omega \notin \Omega_i \end{cases}$$

where P is the standard CES price index faced by the representative consumer.[28] Aggregating the demand from individual consumers, we obtain the demand received by the firm f from destination d at time t:

$$q_{fdt} = q(\lambda_{ft}, X_{dt}, n_{fdt}, p_{fdt}, \varepsilon^D_{fdt}) = n_{fdt}\exp(\lambda_{ft} + X_{dt} + \varepsilon^D_{fdt})p^{-\sigma}_{fdt} \tag{1.4}$$

where X_{dt} will capture all the aggregate variables of the demand shifter,[29] p_{fdt} is the factory price of the good, and ε^D_{fdt} is a random demand shock.

It is important to note that the appeal of the product λ_{ft} does not vary across destinations. Given the existence of an aggregate demand shifter, this implies that firms cannot vary the relative quality or appeal of their good across destinations. Therefore, this specification can still explain that firms will provide different product appeal in different destinations, as long as these differences are common across firms. This assumption will be fundamental to explain the identification assumption of the model: while λ_{ft} and X_{dt} are respectively firm and destination specific, the customer share n_{fdt} will be identified through the sales of a firm in a specific destination.

After describing the demand faced by firms, I now turn to the costs associated with production and international trade.

[28] Note that by having different sets of goods, each consumer would have a different price index. However, I follow Arkolakis (2010) by assuming that each consumer has probabilistically an equivalent set of goods, such that all consumers have the same price index defined as $P = \left[\int_{\omega\in\Omega} n(\omega)\exp(\lambda(\omega))\tilde{p}(\omega)^{1-\sigma}d\omega\right]^{\frac{1}{1-\sigma}}$

[29] $X_{dt} \equiv \log Y_{dt} - (1-\sigma)\log P_{dt} + (1-\sigma)\log(\tau_{dt}e_{dt})$ where $Y_{dt} \equiv yN_{dt}$ are total expenditures from a number of consumers N_{dt}, and τ_{dt} and e_{dt} are respectively iceberg transportation costs and exchange rates that converts the factory price to the consumer price.

1.3.2 Technology and costs

The costs that are associated with production and international trade are similar to those traditionally assumed in the literature. I first describe the constant marginal costs of production, then the fixed costs associated with the exporting activity.

First, I assume constant marginal costs of production. These marginal costs are a decreasing function of the productivity of the firm ϕ_{ft}, and will depend on the appeal of the good produced through a parameter α that characterizes the cost elasticity of appeal. Moreover, I assume the existence of non-persistent productivity shocks ε^S_{fdt}, and I allow costs to vary with the destination market by including a set of coefficients γ_d. Formally, the marginal cost function of the firm is

$$c_{fdt} = c(\phi_{ft}, \lambda_{ft}, \varepsilon^S_{fdt}) = \exp(-\phi_{ft} + \alpha\lambda_{ft} + \varepsilon^S_{fdt} + \gamma_d) \tag{1.5}$$

In addition to these production costs, I will assume that firms need to pay entry and per-period fixed cost for each destination they respectively enter or export to. These fixed costs are defined as follows

$$FC_d + \nu_{fdt} = \begin{cases} f_d + \nu_{fdt} & \text{if} \quad \mathcal{I}_{fdt-1} = 1 \\ f_d + fe_d + \nu_{fdt} & \text{if} \quad \mathcal{I}_{fdt-1} = 0 \end{cases}$$

where $\mathcal{I}_{fdt}$ is a dummy that equals one if the firm f is active (records positive sales) in destination d at time t, and ν_{fdt} is a random shock on fixed costs. I will assume that this shock ν_{fdt} will follow a logistic distribution with variance parameter σ_ν. The addition of this shock will allow the model to rationalize all observed decisions made by the firms. Moreover, it is important to note that the amplitude of these fixed costs will vary across destinations. However, I will restrict this variation in the estimation, by allocating each foreign destination to specific groups sharing the same value of fixed costs.[30]

This achieves the definition of the demand and supply characteristics of the firm. I now turn to the definition of the profit and value functions associated to the exporting activity of firm.

[30] For instance I will assume that entry and per-period fixed costs will be similar for all European countries. Morales, Sheu, and Zahler (2014) develop a specific empirical procedure that allows them to flexibly estimate entry and fixed costs across destinations.

1.3.3 Profit and value function

From the demand received by the firm, and the costs associated with production, I derive the potential profit of the firm for each destination market. After defining the timing of a typical period, I can define the entry problem of the firm, and the associated value functions. This dynamic problem will depend on five variables that will define the state space of the problem: the exogenous variables, that gathers product appeal λ, productivity ϕ and aggregate demand X, the share of consumer n, and the presence on the market in the previous year $\mathcal{I}_{-1}$.

In this model, the decisions of the firms are limited. They can decide whether to be active on the market, and the price they will charge if they decide to export. Consequently, the appeal of the product, the productivity and the aggregate demand from each destination will be exogenous but persistent variables that will potentially capture the hysteresis of the exporting decisions. For ease of exposition, I will denote these variables $\xi \equiv (\lambda, \phi, X)$ such that, ignoring the subscripts and the parameters of the model, the profit function of a firm is

$$\begin{aligned} \Pi(\xi, n, p, \varepsilon, \mathcal{I}_{-1}, \nu) &= q(\xi, n, p, \varepsilon^D) \left[p - c(\xi, \varepsilon^S)\right] - FC(\mathcal{I}_{-1}) - \nu \\ &= \pi(\xi, n, p, \varepsilon) - FC(\mathcal{I}_{-1}) - \nu \end{aligned}$$

where $\mathcal{I}_{-1}$ is a dummy equal to one if the firm was selling on the market in the previous year. This profit function is made of a variable profit and fixed costs. Despite having CES preferences, this variable profit could be negative because of the dynamic nature of the pricing decision of the firm: some firms could set a price lower than their marginal costs to foster future demand. The second part of the profit function comes from the fixed costs of exporting $FC(\mathcal{I}_{-1})$ that will depend on the past presence of the firm on the market. Finally, the profit shock ν will allow the empirical model to explain the entry and exit decisions of firms that cannot be rationalized by the values of the variable profit and fixed costs.

However, this profit will only be obtained by the firm if it decides to be active on the market at this period. In order to study the problem of the firm, it is necessary to define the timeline of a typical period, which provides the timing at which decisions are made and the information sets available to the firms when they make these decisions. Figure 1.4 displays the timeline of a period that defines the dynamic problem of the firm.

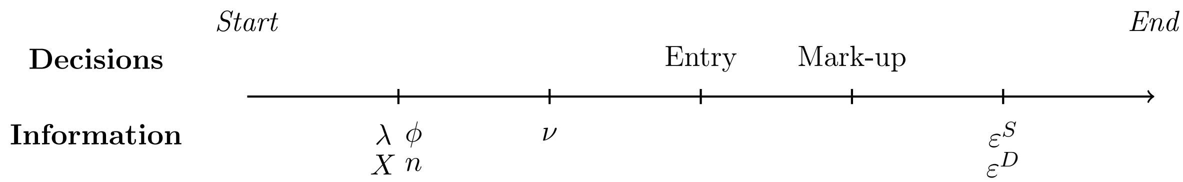

FIGURE 1.4: Timeline of one period

As described in figure 1.4, the firm observes at the beginning of the period its exogenous variables, λ, ϕ, n and X. After realization of the profit shock ν, it decides whether to export in the market. If the firm decides to export, it optimally chooses the mark-up to charge over their marginal costs.[31] Finally, sales and prices will be obtained after observing the realization of the non-persistent shocks ε.[32]

Therefore, denoting μ the multiplicative mark-up of the firm such that $p = \mu c$, the value function of the firm can be defined as the following:

$$
\begin{aligned}
V(\xi, n, \mathcal{I}_{-1}) &= E_\nu \max \Big\{ V_I(\xi, n) - FC(\mathcal{I}_{-1}) - \nu \ ; \ V_O(\xi) \Big\} \\
\text{with} \qquad V_I(\xi, n) &= \max_{\mu} \Big\{ E_\varepsilon \Big\{ \pi(\xi, n, \mu, \varepsilon) + \beta EV'(\xi, n'(\xi, n, \varepsilon, \mu), 1) \Big\} \Big\}, \\
V_O(\xi) &= \beta EV'(\xi, n_0, 0), \\
EV'(\xi, n', \mathcal{I}) &= \int_{\xi'} V(\xi', n', \mathcal{I})\, dF(\xi'|\xi).
\end{aligned}
$$

The first line describes the entry problem, in which the firm chooses between exporting $V_I(\xi, n) - FC(\mathcal{I}_{-1})$ and inactive $V_O(\xi)$. By being inactive, the firm makes no profit today but retains the possibility to update its decision in the next period. In contrast, when exporting, it obtains a present profit that will depend on the shocks ε and the mark-up chosen by the firm. Moreover, the firm will have a continuation value, $EV'(\xi, n'(\xi, n, \varepsilon, \mu), 1)$, characterized by a stock of consumer n'

[31] Choosing the mark-up rather the price facilitates the computation of the solution, while allowing for structural shocks ε in demand and costs.

[32] The assumptions made regarding the timing of the shocks and decisions are mostly driven by the construction of the empirical model. The realization of the shock ν before the entry decisions allow the model to rationalize entry decisions that couldn't be explained otherwise. Similarly, the realizations of the shocks ε after the markup decisions generate structural errors in the sales and prices equations that can explain sales and prices variations.

and lower fixed costs to pay in the next period. This continuation value will be constructed from the transition of the exogenous variables $F(\xi'|\xi)$, and the expected value of $V(\xi, n', I)$.

In order to solve this problem, it is necessary to proceed through backward induction by describing the pricing decision made by the firm once it enters. This optimal pricing decision leads to the expected profit of the firm, and therefore solves for the entry decisions. I describe these optimal decisions and the value functions of the problem in the next subsection.

1.3.4 Firms' decisions: entry and pricing.

After defining the problem of the firm, I can now derive the optimal entry and pricing decisions of the firm. Because the accumulation of consumers is based on the sales of the firm, the optimal price charged by the firm will deviate from a standard constant mark-up. Instead, firms will optimally reduce their mark-up to account for the accumulation of consumers. Because this pricing decision is taken once the firm has decided to enter, I start by describing the optimal mark-up charged by the firm. By backward induction, I will infer the expected profit of the firm conditional on this optimal pricing decision, and therefore infer the value and probability of exporting.

Optimal price The choice of the mark-up of the firm involves solving a dynamic problem: by affecting the sales of the firm today, the price charged by the firm affects the share of consumers tomorrow. Therefore, the firm will have incentives to reduce its price today to foster the accumulation of future consumers.

The choice of mark-up of the firm is made after entry, in order to maximize the sum of the present profit and the continuation value of exporting. Formally, the problem and first-order conditions are the following:

$$\begin{aligned} V_I(\xi, n) &= \max_{\mu} \Big\{ E_\varepsilon \Big\{ \pi(\xi, n, \mu, \varepsilon) + \beta E V'(\xi, n'(\xi, n, \varepsilon, \mu), 1) \Big\} \Big\} \\ \Longrightarrow \qquad & E_\varepsilon \Big\{ \frac{\partial \pi(\xi, n, \mu, \varepsilon)}{\partial \mu} + \beta \frac{\partial n'}{\partial \mu} \frac{\partial E V'(\xi, n', 1)}{\partial n'} \Big\} = 0 \end{aligned}$$

Therefore, the optimal price of the firm is:

$$p(\xi,n) = \mu(\xi,n)c(\xi,n) \tag{1.6}$$

$$\text{with} \qquad \mu(\xi,n) = \frac{\sigma}{\sigma-1}\frac{1}{1+\beta E_{w(\varepsilon)}\{\eta_1(1-n')^{\psi}\frac{\partial EV'(\xi,n',1)}{\partial n'}\}}$$

The optimal mark-up charged by the firm has two components. First, the firm will apply the standard CES mark-up $\frac{\sigma}{\sigma-1}$ based on the price-elasticity of the demand. Second, the firm will apply a discount factor based on the dynamic incentives it has to lower its price to attract more consumers in the future. This factor will depend on two elements: first, how much this increase in sales will increase its consumer share tomorrow, $\eta_1(1-n')^{\psi}$; this element will induce lower mark-ups for small or young firms that benefit from higher returns of accumulation. Second, the extent of this discount will also depend on the impact of this increase in the future consumer share on the continuation value $\frac{\partial EV'(\xi,n',1)}{\partial n'}$. This effect will not be linear but hump shaped with the profitability of the firm:[33] young firms that are unlikely to survive will not have incentives to invest in future consumers. Firms that can use extra consumers to increase their probability of survival will get the largest benefits from increasing their consumer share. However, because of the concavity of the value function conditional on surviving, this effect will be smaller for high profit firms that are likely to survive in the next period. Finally, note that this equation defines the unique optimal price charged by the firm but only through an implicit function, since the future share n' will depend on the price charged.[34]

Consequently, the accumulation of consumers will imply heterogeneous mark-ups by the firms, depending on their current share of consumers, and their expectations on future profits. Having

[33] This comes directly from the probability of exit that makes the value function of the firms increasing and convex for low profitability firms, and increasing and concave for higher profit firms.

[34] Note that

$$E_{w(\varepsilon)}\left\{\eta_1(1-n')^{\psi}\frac{\partial EV'(\xi,n',1)}{\partial n'}\right\} \equiv \int_{\varepsilon}\frac{c(\xi,\varepsilon)q(\xi,n,\mu,\varepsilon)}{\int_{\varepsilon}c(\xi,\varepsilon)q(\xi,n,\mu,\varepsilon)}\eta_1(1-n')^{\psi}\frac{\partial EV'(\xi,n',1)}{\partial n'}dF(\varepsilon)$$

To overcome the absence of closed form solution for the optimal price, I will use a grid to solve the optimal price of the firm in the estimation procedure. Moreover, solving the dynamic problem of the firm will also be facilitated by assuming that $E_{\varepsilon}EV'(\xi,n'(\xi,n,\varepsilon,\mu),1) = EV'(\xi,n'(\xi,n,E_{\varepsilon}\varepsilon,\mu),1)$. This assumption will allow me to redefine the problem such that

$$V_I(\xi,n) = \max_{\mu}\left\{E_{\varepsilon}\left\{\pi(\xi,n,\mu,\varepsilon)+\beta EV'(\xi,n'(\xi,n,\varepsilon,\mu),1)\right\}\right\} = \max_{\mu}\left\{E_{\varepsilon}\pi(\xi,n,\mu,\varepsilon)+\beta EV'(\xi,\bar{n}'(\xi,n,\mu),1)\right\}$$

for which $E_{\varepsilon}\pi(\xi,n,\mu,\varepsilon)$ admits a closed-form solution that will facilitate the evaluation of the model.

described the optimal mark-up of the firm, it is possible to infer the expected profit of the firm in case of entry. Therefore, I can evaluate the two options of the firm, and study its entry decision.

Entry condition Knowing the expected option values of being active or inactive, I can now study the entry decision of the firm. The firm will pick the most profitable option, after observing the shock ν that affects the fixed costs of being active on a market. The logistic assumption for this shock will generate a closed-form solution for the probability of entry, but also for the expected value function before observing this shock. Formally, the expected value of the firm before observing the shock ν is

$$\begin{aligned} V(\xi, n, \mathcal{I}_{-1}) &= E_\nu \max \left\{ V_I(\xi, n) - FC(\mathcal{I}_{-1}) - \nu \;\; ; \;\; V_O(\xi) \right\} \\ &= \sigma_\nu \log \left[\exp\left(\frac{1}{\sigma_\nu} \big(V_I(\xi, n) - FC(\mathcal{I}_{-1}) \big) \right) + \exp\left(\frac{1}{\sigma_\nu} V_O(\xi) \right) \right]. \end{aligned}$$

This equation closes the dynamic problem of the firm, by providing the fixed point that defines the value function $V(\xi, n, \mathcal{I}_{-1})$. Moreover, the probability for a firm to be active, before the realization of the fixed cost shock ν, is,

$$P(\mathcal{I} = 1 | \xi, n, \mathcal{I}_{-1}) = \frac{1}{1 + \exp\left(-\frac{1}{\sigma_\nu} \left(DV(\xi, n) - FC(\mathcal{I}_{-1}) \right) \right)} \tag{1.7}$$

with $DV(\xi, n) = V_I(\xi, n) - V_O(\xi)$. This last equation predicts the probability of entry of a firm, conditional on its current characteristics, described by ξ, n and $\mathcal{I}_{-1}$. While n and $\mathcal{I}_{-1}$ are endogenous, ξ are exogenous and unobservables variables. Therefore, to finish the derivation of the model, it is necessary to describe the evolutions of these exogenous variables across time. These evolutions will be important to compute the expectation of the value functions, $EV'(\xi, n, \mathcal{I}_{-1})$, as well as disciplining the variations of sales and prices across times in the empirical application.

1.3.5 Evolution of exogenous variables

In order to close the definition of the dynamic problem of the firm, I need to specify the evolution of the exogenous variables of the model. These exogenous variables will be important as they can account for a large amount of the persistence in export decisions observed in the data. Most of the hysteresis in exporting decisions is likely to come from the persistence over time of fundamental characteristics of the firm such as productivity or product appeal. Therefore, it is necessary to allow these processes to be persistent. Moreover, to account for the important attrition rate across ages, it is also necessary to let these processes vary across time, through random shocks. Consequently, one wants to assume general processes that are time variant, and allow for important persistence in their evolution. For these reasons, I will assume that these three variables will follow AR(1) processes, with flexible parameters. Formally, I assume

$$\begin{aligned} \lambda_{ft} &= \rho_\lambda \lambda_{ft-1} + \sigma_\lambda \varepsilon^\lambda_{ft} \\ \phi_{ft} &= \mu_\phi + \rho_\phi \phi_{ft-1} + \sigma_\phi \varepsilon^\phi_{ft} \\ X_{dt} &= \mu_{Xd} + \rho_X X_{dt-1} + \sigma_X \varepsilon^X_{dt} \end{aligned} \tag{1.8}$$

where the ε shocks follow a normal distribution with zero mean and unit variance. Note that, by normalization, λ is centered around zero: since both X and λ enters linearly in the demand function, it is not possible to separately identify their respective means. Moreover, because X_{dt} describes the aggregate demand from a destination d, I allow the mean μ_{X_d} of this process to change across destination. This will allow the model to capture different trends in aggregate demand across different destinations.

Finally, I need to impose distributional assumptions on the initial conditions of these unobservables. I assume that the distributions of product appeal and productivity are stable over time such that the initial distributions are constrained by a stationary assumption. Consequently, we have

$$\begin{aligned} \lambda_{f0} &\sim N\left(0, \frac{\sigma_\lambda}{\sqrt{(1-\rho_\lambda^2)}}\right) \\ \phi_{f0} &\sim N\left(\frac{\mu_\phi}{1-\rho_\phi}, \frac{\sigma_\phi}{\sqrt{(1-\rho_\phi^2)}}\right) \end{aligned} \tag{1.9}$$

However, I will assume that the variation in aggregate demand across destinations does not arise from a stationary distribution. Therefore, I will assume a flexible distribution of initial conditions for X_{d0} such as

$$X_{d0} \sim N(\mu_{X_0}, \sigma_{X_0}). \tag{1.10}$$

Moreover, I will assume that the initial share of consumers, which will apply to firms that records positive sales the year before the beginning of the model, follow a Beta distribution with parameters 1 and 5.[35]

This concludes the derivation of the model. Each firm observes exogenous variations in its export profitability through variation in its productivity, product appeal and the demand in each destination. Based on these variations, the firm decides to enter or exit various destinations where it decides at which prices to sell its good. The more the firm sells on a market, the more consumers will be ready to buy from it in the next period, fostering its demand and profit in the next period. After describing the model, I now describe the restrictions I impose to obtain a model without consumer accumulation, that will behave similarly to standard models used in the literature.

1.3.6 Restricted model

In order to assess the importance of consumer accumulation on estimated trade costs and aggregate response to trade, I will estimate a restricted version of the model that does not feature this mechanism. This restricted model is equivalent to assuming that exporters will have a consumer share n_{fdt} equal to one when they are active on the market. As a consequence, firms will not have incentives to deviate from the CES pricing, and the mark-ups will be similar across all firms.

This restricted version of the model can be seen as the canonical model used in the literature. In this model, firm-level heterogeneity and entry costs of exporting explain the hysteresis in exporting. This model can be seen as a dynamic version of Melitz (2003), as estimated by Das, Roberts, and Tybout (2007). Estimating this restricted model will be essential to assess the importance of the accumulation of consumers on the outcomes of the estimation and the aggregate implications of the model.

1.4 Estimation

In this section, I describe the procedure used to estimate the parameters of the model. The likelihood is directly obtained from the three structural equations of the model. However, the evaluation of

[35] Given the number of firms in this case, and the length of the panel I will use (14 periods), this assumption has no consequence on the estimation.

this likelihood is made cumbersome by the number of persistent and unobservables variables and the dynamic problem of the firm.

I start by describing the likelihood of the problem, based on the three structural equations linked with the observable variables (sales, prices and participation to export). I then turn to the algorithm to show the advantages of a MCMC estimator to facilitate the estimation of the model. Finally, I provide the intuition behind the identification of the parameters and unobservables of the model.

1.4.1 Likelihood

I start by presenting the likelihood that is obtained from the three main equations of the model: the demand equation in which the stock of consumers of the firm appears, the pricing equation that features the dynamic mark-up charged by the firm, and the entry probability that describes the exporting decision on each destination.

First of all, the demand and price equations (1.4), (1.5) and (1.6) are taken in logarithm to obtain

$$\begin{aligned}
\log s_{fdt} &= \log n_{fdt} + \lambda_{ft} + X_{dt} + (1-\sigma)\log p_{fdt} + \varepsilon^{D}_{fdt} \\
\log p_{fdt} &= -\phi_{ft} + \alpha\lambda_{ft} + \log\mu(\xi, n_{fdt}) + \gamma_d + \varepsilon^{S}_{fdt}
\end{aligned}$$

This block will constitute the first part of the likelihood. Assuming that ε follows a bivariate normal distribution with variance Σ, I define this likelihood block as $L_\varepsilon(s_{fdt}, p_{fdt}|\xi_{fdt}, n_{fdt}; \Theta)$,[36] with Θ being the full set of parameters, such that

$$\begin{aligned}
L_\varepsilon(s_{fdt}, p_{fdt}|\xi_{fdt}, n_{fdt}; \Theta) = G_\Sigma\Big(& \log s_{fdt} - \log n_{fdt} - \lambda_{ft} - X_{dt} - (1-\sigma)\log p_{fdt}\ ; \\
& \log p_{fdt} + \phi_{ft} - \alpha\lambda_{ft} - \log\mu(\xi, n) - \gamma_d \Big)
\end{aligned} \tag{1.11}$$

where G_Σ is the density function of a bivariate normal distribution with means zero and variance matrix Σ.

The second block of the likelihood will be based on the entry decision of the firm. Equation

[36] As previously defined, ξ_{fdt} gathers all the exogenous variables of the model - product appeal, productivity and aggregate demand - such that $\xi_{fdt} \equiv \{\lambda_{ft}, \phi_{ft}, X_{dt}\}$

(1.7) defines the probability to enter for a firm, based on its set of unobservables ξ, its stock of consumer n and its past exporting activity. I denote this function $L_\nu(I_{fdt}|\xi_{fdt}, n_{fdt}, I_{fdt-1}; \Theta)$ that is obtained from the binary choice made by the firm

$$\begin{aligned} L_\nu(\mathcal{I}_{fdt}|\xi_{fdt}, n_{fdt}, \mathcal{I}_{fdt-1}; \Theta) = &\left[1 + \exp\left(\frac{-DV(\xi_{fdt}, n_{fdt}) + FC(\mathcal{I}_{fdt-1})}{\sigma_\nu}\right)\right]^{-\mathcal{I}_{fdt}} \\ &\times \left[1 + \exp\left(\frac{DV(\xi_{fdt}, n_{fdt}) - FC(\mathcal{I}_{fdt-1})}{\sigma_\nu}\right)\right]^{\mathcal{I}_{fdt}-1} \end{aligned} \tag{1.12}$$

where function $DV(\xi_{fdt}, n_{fdt})$ and $FC(\mathcal{I}_{fdt-1})$ are defined as previously. Therefore the total likelihood for a given observation $D_{fdt} \equiv \{s_{fdt}, p_{fdt}, \mathcal{I}_{fdt}\}$ is

$$L(D_{fdt}|D_{fdt-1}, \xi_{fdt}, n_{fdt-1}; \Theta) = L_\nu(\mathcal{I}_{fdt}|\xi_{fdt}, n_{fdt}, \mathcal{I}_{fdt-1}; \Theta) \times L_\varepsilon(s_{fdt}, p_{fdt}|\xi_{fdt}, n_{fdt}; \Theta).$$

To obtain the unconditional likelihood, that does not depend on the unobservables of the model, it is necessary to integrate out this set of unobservables. However, because these unobservables are persistent over time, the likelihood of the entire dataset D is obtained by repeatedly integrating the unobservables from period T to 0. Formally, the full likelihood is

$$\begin{aligned} L(D|D_{-1}; \Theta) = \int_{n_{-1}} \int_{\xi_0} \ldots \int_{\xi_T} \prod_{f,d} &L(D_{fdT}|D_{fdT-1}, \xi_{fdT}; \Theta) \times \ldots \times L(D_{fd0}|D_{fd-1}, \xi_{fd0}, n_{fd-1}; \Theta) \\ &dF(\xi_{fdT}|\xi_{fdT-1}) \times \ldots \times dF(\xi_{fd0})\, dF(n_{fd-1}) \end{aligned}$$

where $F(\xi_{fd0})$ is defined by the density of the initial unobservables defined in equations (1.9) and (1.10), and $F(n_{fd-1})$ the beta distribution assumed for firms that were exporting the year before the beginning of the estimation sample, and D_{fd-1} the observables previous to the estimation sample. After describing the likelihood of the problem, I now turn to the estimation procedure by describing the algorithm aiming to find the posterior distribution of parameters Θ.

1.4.2 Algorithm

To estimate the model, I develop a Markov Chain Monte Carlo (MCMC) estimator to account for two important difficulties in evaluating the likelihood of this problem: the different sources of persistent and unobservable heterogeneity and the dynamic problem of the firm. First, the persistent unobservable characteristics make it necessary to perform a large number of integration in order to evaluate the likelihood. This is particularly cumbersome given the persistent nature of these sources of heterogeneity. The second difficulty comes from the need to solve for the value functions in order to obtain the objects $DV()$ and $\mu()$ and evaluate the likelihood. The literature on dynamic discrete choices model, starting from Rust (1987) is mostly devoted to this specific problem, which requires obtaining the solution of the Bellman equation through value function iterations until reaching a fixed point.[37] Therefore, even in the absence of unobservables, the likelihood function is a highly non-linear function of the parameter set Θ, increasing the difficulty, and the computing time, of evaluating the likelihood.

In order to circumvent these difficulties, I employ a MCMC estimator, taking advantage of recent Bayesian techniques to sample the posterior distribution of the parameter Θ, conditional on the data. The choice of a Bayesian estimator relies on two recent findings from the Bayesian econometrics literature. First, Arellano and Bonhomme (2009) show how Bayesian hierarchical models nest fixed and random effects models: using a prior distribution of the unobservable of the model, the posterior distribution of the unobservable term will be very precise when many observations are available (for instance when one firm sells to many destinations), such that this posterior distribution will be close to the fixed effects value. When the number of observations is limited (for instance when a firm only sells to one country), the prior distribution of the unobservable variable, as specified by the model, will constrain the value of this variable similar to the random-effect case. Moreover, using MCMC in this context will allow one to perform the integration by updating unobservables as latent variables of the model. Therefore, a Bayesian estimator offers a attractive way of integrating these unobservables, while correcting for the first-order bias that exists in fixed and random-effects models.[38]

Second, to overcome the computational burden of solving the value functions in the likelihood, Imai, Jain, and Ching (2009) and Norets (2009) show how to take advantage of the iterative feature of the MCMC estimator, by only updating the value functions in the Bellman equation once at each

[37]This problem can be largely simplified using the mapping between conditional choice probabilities and value functions, as highlighted in Hotz and Miller (1993). However, in my application where state variables are mostly unobserved, obtaining conditional choice probabilities in a first step is not trivial, and likely to be an imprecise exercise.

[38]Roberts, Xu, Fan, and Zhang (2012) also use this type of estimator in a similar context. The main difference being that the unobservables terms are time-invariant in their model while they vary in mine, making the integration issue even more stringent in my setup.

iteration. The intuition is that there is no need to fully solve for the fixed point of the value function at each point of the parameter set. Instead, it is possible to only iterate the Bellman equations a limited number of times at each iteration of the Markov chain, reusing these value functions as initial values for the next iteration. As the Markov chain converges and explores the posterior distribution of Θ, the value function will also converge toward the fixed point that solves the Bellman equation.

Overall, the MCMC estimator will explore the posterior distribution of the parameters Θ. This distribution is proportional to the product of the likelihood and the prior distribution such that

$$P(\Theta \mid D) \propto \int_{\xi} L(D \mid \xi, \Theta)\, dF(\xi \mid \Theta)\, P(\Theta) \tag{1.13}$$

where $L(D \mid \Theta) = \int_{\xi} L(D \mid \xi, \Theta)\, dF(\xi \mid \Theta)$ is the likelihood of the problem and $P(\Theta)$ is the prior distribution of the parameter set. Because I do not want these priors to influence the posterior distribution of the parameters, I will assume that all the priors are flat, except for values of parameters that do not satisfy theoretical or stationarity constraints.[39] Therefore, the goal of the Markov Chain is to repeatedly sample from the posterior distribution according to (1.13). This will be achieved by alternatively sampling parameters conditional on unobservables, and parameters conditional on unobservables. In this specific application, an iteration in the Markov chain consists of three different steps, summarized in the following iteration.

At an iteration s, the inputs of the Markov chain are $\Theta^{(s)}, \xi^{(s)}$ and the history of value functions $\left\{V(\Theta^{(h)})\right\}_{h=s-m}^{s}$ and their associated parameters sets $\left\{\Theta^{(h)}\right\}_{h=s-m}^{s}$ for a given $m \geq 0$. The steps of a typical iteration are:

- Sample $\xi^{(s+1)}$ proportionally to $L(D|\xi, \Theta^{(s)}) f(\xi|\Theta^{(s)})$
- Sample $\Theta^{(s+1)}$ proportionally to $L(D|\xi^{(s+1)}, \Theta) f(\xi^{(s+1)}|\Theta) P(\Theta)$
- Update $\left\{V(\Theta^{(h)}), \Theta^{(h)}\right\}_{h=s+1-m}^{s+1}$ using $\Theta^{(s+1)}$ and $V(\Theta^{(s+1)})$.

Two important points are worth noticing regarding this algorithm. First, the large size of the parameter space requires updating the parameters sequentially rather than simultaneously. In total,

[39] I exclude from the support of Θ (or equivalently assigned a prior probability of zero for these values), negative values for the variance parameters, as well as values beyond -1 and 1 for the autocorrelation parameters. Finally, I also impose the average fixed cost and entry cost parameters (f, fe) to be positive. and the parameter ψ to be larger than zero.

30 parameters will be estimated in the model. Consequently, a Gibbs sampling is used in which different parameters blocks are created and sequentially updated based on the different blocks of the likelihood.[40] Second, the value functions that allow the computation of the objects $DV(.)$ and $\mu(.)$ will be obtained on a grid that will be updated throughout the algorithm. The specific values of $DV(.)$ and $\mu(.)$ will then be obtained by interpolation to be evaluated at any point in the state space. I provide extensive details in appendix A.3 about the implementation of the algorithm.

Due to the complexity of the estimation procedure, two parameters will not be estimated and set to specific values from the literature. First of all, I do not estimate the value of β, the discount rate of future periods. This parameter is difficult to identify in dynamic discrete choice models and I therefore set its value to 0.9, following Das, Roberts, and Tybout (2007).[41] Second, I do not estimate the elasticity of substitution of the CES utility function. Estimating the price-elasticity of demand using trade data is not trivial given the absence of product characteristics, which implies unobserved vertical differentiation across goods.[42] Therefore, I will use the value obtained by Broda and Weinstein (2006) for the corresponding industry; they estimate an elasticity of 2.2 for the wine industry, which I will utilize and keep constant throughout the algorithm.

After describing the details of the estimation procedure, I provide, in the next section, intuition about the sources of identification of the parameters and the unobservables.

1.4.3 Identification intuition

Despite the complexity of the algorithm, estimating this model using micro data and a full information estimator provides simple intuitions of the identification of the parameters. Moreover, the alternative sampling of unobservables and parameters shed light on the separate sources of identifications of each component of the likelihood.

To describe the sources of identification, it is important to distinguish the identification of unobservables and parameters. Let's assume first that the parameters of the model are known. In this situation, the identification of the unobservables mostly come from a variance decomposition

[40] Despite the separation of the parameters in different sets, the existence of value functions in the likelihood creates a dependence between most parameters of the parameter set and the different part of the posterior distribution. Therefore, Metropolis-Hastings algorithms are used to sequentially update these different blocks.

[41] Magnac and Thesmar (2002) provides an extensive discussion of identification issues in DDCM.

[42] See Piveteau and Smagghue (2015) for a discussion on the estimation of this elasticity. In theory, prices in other destinations could be used as instrument for the prices. However, this requires controlling for the impact of quality on marginal costs, which is part of the model (through the parameter α).

of the demand shifters and prices. Indeed, knowing sales and prices, the demand shifter is decomposed between a firm-year component (the product appeal λ_{ft}), a destination-year component (the aggregate demand X_{ft}), and a firm-destination-year component (the consumer base n_{fdt}). Once the product appeal is known, the productivity ϕ_{ft} is identified by price variations across firms. Therefore, the identification of the unobservables mostly comes from a decomposition of observables variables, which is straightforward once the parameters of the model are known. Moreover, the hierarchical structure and the entry decisions will bring additional information to identify the posterior distribution of these unobservables. For instance, if a firm is not exporting one year, the information from previous and future years will help identify the potential value of the unobservables. Similarly, the entry decisions in foreign destinations will bring additional information about the posterior distribution of these unobservables: if a firm only exports to one destination at a given year, the fact that it does not export somewhere else will provide information regarding the latent value of its product appeal or productivity.

Let's now turn to the identification of the parameters of the model, assuming that the unobservables are known. The 30 estimated parameters can be divided in three groups: 17 of them are related to the laws of motion of the unobservables, 6 to the demand and supply equations, and 7 related to the dynamic problem of the firm. Knowing the unobservables of the problem, the identification of the parameters that describes their distribution and law of motions is straightforward. Regarding the parameters that are linked to the demand and pricing functions, their identification is similar to a regression of prices on destination dummies and the appeal of the product, while the parameters of the variance matrix are obtained from the variance of the unexplained variation in prices and sales. Finally, the parameters related to the entry problem of the firm are obtained by comparing potential profits and firms' observed decisions. Based on the characteristics of the firms and destinations, the laws of motion of unobservables, and the parameters of the cost and demand functions, it is possible to construct the potential profit of each firm on each market. Based on these potential profits, the number of exporters will identify the per-period fixed costs, the persistence in exporting the entry costs, and the remaining variance in exporting decisions will identify the required variance of these fixed costs' shocks.

Consequently, the identification of the unobservables conditional to the parameters, and of the unobservables conditional to the unobservables are quite straightforward. The goal of the MCMC estimator is to repeatedly sample each component conditional to the other, in order to obtain their joint distribution. After a necessary period of convergence, the Markov Chain will describe the posterior distributions of the parameters.

1.5 Results

I implement my estimation on a set of wine exporters from France; the choice of the industry is based on two criteria. First, wine producers only export wine. Therefore, it is reasonable to assume that the entry decisions on foreign destinations are made at the firm level, and it is possible to aggregate sales and prices at the level of the firm for each destination. Second, the wine industry is a large industry in France and, therefore, I can obtain a large enough sample of exporters with a relatively extended set of destinations. In appendix A.1.2, I describe the specific selection procedure to obtain the estimation sample of 200 firms, and provide statistics to describe this sample.

In order to describe the results of the estimation, I start by describing the fit of the model relative to the exporters' dynamics presented earlier. Then I will present the estimated values of the parameters, and in particular the decrease in entry costs induced by the introduction of the consumer margin. Finally, I will describe the evolution of the consumer margin and the mark-ups charged by firms at different export ages.

1.5.1 Fit of the model

I report in this section the fit of the model regarding the survival rates, sales and prices of the firm-destination pair at different ages. Figure 1.5 reports the predictions of the model relative to the data. I also report the results of the restricted version of the model, which does not contain a consumer margin.

As reported in figure 1.5, the full model with consumer accumulation can reproduce most of the growth in sales across ages (top left figure). The ability of the model to capture this growth explains how the model can perform better in terms of survival rates (top right figure): as a firm accumulates more consumers in a foreign destination, raising its sales, it also increases its future profit, and therefore its survival rate. However, this growth in sales is not sufficient to fully explain the low survival rates of young exporters, and, therefore, does not entirely solve the puzzle linked

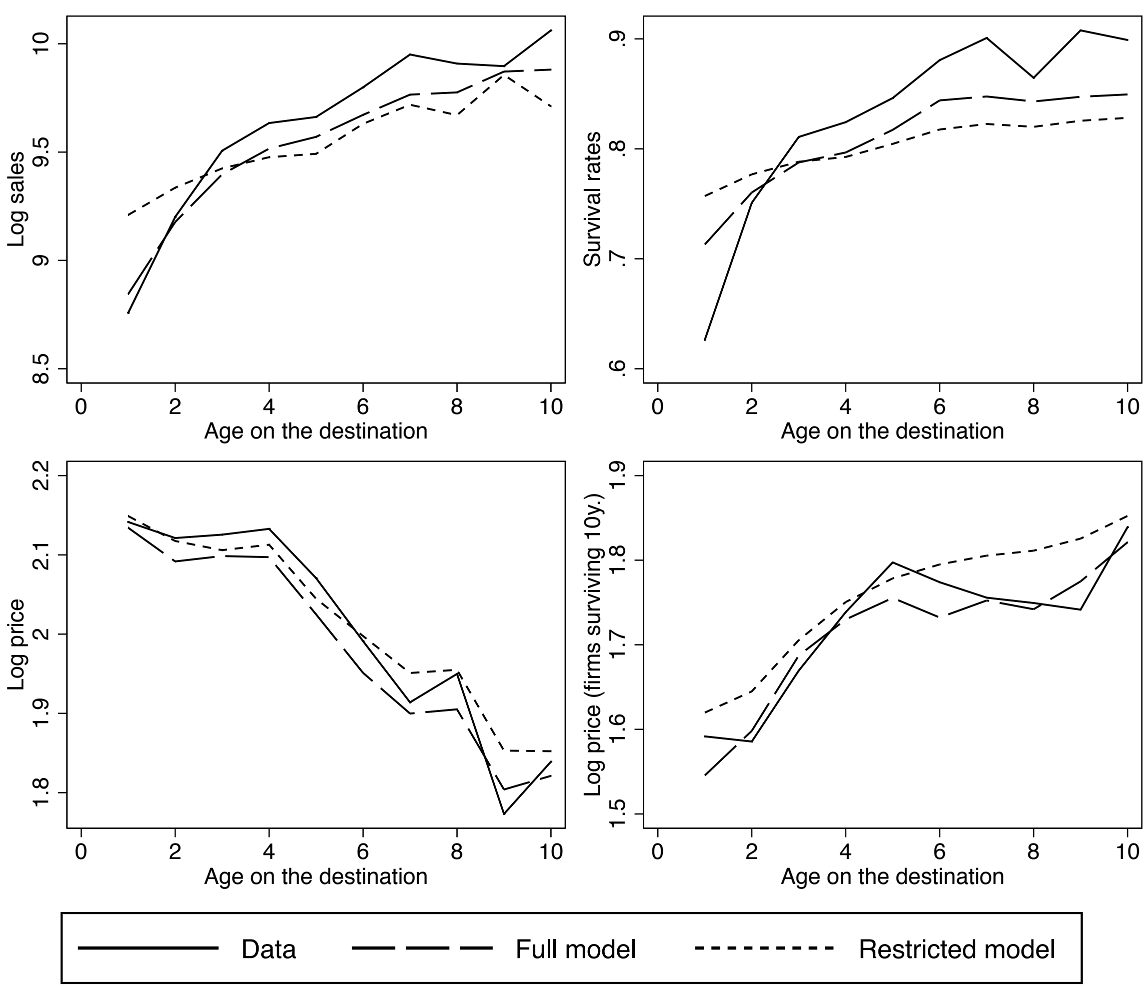

Figure 1.5: Predictions of survival rates, sales and prices across ages.

with young exporters dynamics. In comparison, the restricted model cannot explain this rise in sales and even less in survival rates: in the restricted model, the predicted survival rate is constant across ages, between 75 and 80 percent, which is similar to the average survival rate in the sample. However, the predictions on prices appear quite similar across models (bottom figures). Both of them can reproduce the decrease in prices with age. When looking at firms surviving 10 years, we can see that the full model can do slightly better in explaining the rise in price with the age of the firm. Therefore, the heterogeneous mark-ups obtained from the dynamic problem of the firm seems to help the model in predicting low prices at young ages.

After describing the fit of the model, I turn to the description of the estimated values of the parameters.

1.5.2 Estimated parameters

The results of the estimation of the model are reported in table 1.2. I report for each parameter the mean of its posterior distribution, as well as its 90 percent confidence interval.

TABLE 1.2: Estimated parameters

Parameter		**Estimate**	**90% Confidence Interval**	
			Lower bound	*Upper bound*
Per-period fixed costs	Europe	7 994	6 761	9 194
(in 2000 euros)	Americas	7 495	6 693	8 304
	Asia/Oceania	8 019	7 080	8 930
Entry fixed costs	Europe	33 730	30 303	37 078
(in 2000 euros)	Americas	23 656	21 092	26 208
	Asia/Oceania	28 619	25 387	31 928
Variance of entry shocks	σ_ν	9 656	8 589	10 620
Law of motion of n	n_0	0.033	0.031	0.034
	$\underline{n}$	0.015	0.014	0.016
	$\eta_1(10^{-5})$	0.12	0.11	0.14
	η_2	0.27	0.23	0.29
	ψ	0.44	0.00	0.93
Law of motion of appeal	ρ_λ	0.98	0.98	0.98
	σ_λ	0.19	0.18	0.20
Law of motion of productivity	ρ_ψ	0.93	0.91	0.94
	σ_ψ	0.09	0.08	0.09
	μ_ψ	-0.12	-0.14	-0.10
Law of motion of agg. demand	ρ_X	0.93	0.93	0.94
	σ_X	0.09	0.09	0.09
	μ_{X1}	0.98	0.91	1.03
	μ_{X2}	0.88	0.74	0.97
	μ_{X3}	0.89	0.77	0.97
	μ_{X_0}	14.58	14.31	14.83
	σ_{X_0}	0.46	0.32	0.65
Elasticity cost of appeal	α	0.73	0.73	0.74
Cost dummies	γ_2	0.38	0.36	0.39
	γ_3	0.30	0.29	0.30
Variance matrix	Σ_{11}	1.25	1.25	1.26
	Σ_{12}	0.17	0.17	0.17
	Σ_{22}	0.56	0.54	0.57

First, looking at the law of motion of the consumer margin, we note that the initial share of consumers at entry (n_0) is relatively small, equal to 3 percent, which leaves a large potential for firms to grow through the accumulation of consumers. This growth is driven both by the past sales of the firm (η_1), as well as the past shares of consumers (η_2), since the two coefficients are significantly larger than zero. Moreover, we can see that the degree of concavity of this law of motion is significant, with a mean of the posterior distribution of the coefficient ψ equal to 0.44.

Second, the other unobservables of the model - appeal, productivity and aggregate demand - depict strong degrees of persistence. The coefficients of autocorrelation of the AR(1) processes are estimated to be in average 0.98, 0.93 and 0.93, respectively for the product appeal, the productivity of the firm, and the aggregate demand of the destination. Moreover, the appeal appears to have a larger variance across firms ($\frac{0.19}{\sqrt{1-0.98^2}} = 0.95$) than productivity ($\frac{0.09}{\sqrt{1-0.93^2}} = 0.24$). If this is not surprising, given that sales have a larger variance than prices, it is interesting to look at the implied contribution of these two unobservables variables to sales. With a parameter of the cost of appeal α equal to 0.73, it means that an extra unit of appeal has an impact of 11 percent $(1 - 0.74 \times 1.2)$ on sales, which is compared to an increase of 100 percent from productivity. Consequently, moving from the average appeal to the 5th best percentile increases the sales by 17 percent, while the same movement for productivity increases sales by 39 percent.

Finally, because I estimate a structural model of entry, the model is able to deliver euro estimates of the sunk fixed costs of entry as well as the per-period fixed costs paid by an exporter.[43] We see that the obtained fixed costs are relatively low, with the entry cost to an European destination being equal to 33 730 euros.[44] In addition, a firm would have to pay 8 000 euros every year to keep exporting to this destination. As an element of comparison, the average export value of a firm in my sample to an European destination is 42 000 euros, while the median value is 13 000. One of the reasons for these relatively low numbers is the small variance parameter of these fixed costs' shocks, whose the average of the posterior distribution is 9 656. This low number reflects the ability of the model to correctly predict the entry and exit of firms, such that a large variance of these fixed costs' shocks is not necessary to rationalize entry decisions.

In order to confirm the small magnitudes of these entry fixed costs relative to the literature,

[43] I separated my destinations into three groups such that each European destination will have similar fixed costs. This does not imply that the firm do not need to pay these costs for each destination it enters. If a firm exports to 5 European destinations, it will have to pay 5 times these fixed costs.

[44] Prices are normalized across years using a national consumer price index, such that the values are expressed as euros from the year 2000.

I compare theses parameters with the ones I obtain when estimating the restricted version of the model, which does not have a consumer margin. Results are displayed in table 1.3.

TABLE 1.3: Estimated parameters (comparison between models)

		Full model			Restricted model		
Parameter		**Estimate**	**90% C.I.**		**Estimate**	**90% C.I.**	
			Lower	*Upper*		*Lower*	*Upper*
Per-period fixed costs	Europe	7 994	6 761	9 194	8 521	7 989	9 080
	Americas	7 495	6 693	8 304	14 605	13 429	15 810
	Asia/Oceania	8 019	7 080	8 930	16 133	14 531	17 997
Entry fixed costs	Europe	33 730	30 303	37 078	98 286	87 044	110 368
	Americas	23 656	21 092	26 208	72 073	63 372	81 393
	Asia/Oceania	28 619	25 387	31 928	80 951	71 094	91 913
Elasticity cost of appeal	α	0.73	0.73	0.74	0.39	0.37	0.41
Variance of entry shocks	σ_ν	9 656	8 589	10 620	25 789	23 121	28 703

The comparison between two models highlights that the entry costs, and more generally the fixed costs of exporting, are much larger in the version without consumer margin. For instance, the average entry costs to export to Europe jump from 33 730 to 98 286 euros. Part of this increase comes from the change in the parameter of variance of the fixed costs from 9 656 to 25 789. This increase is a reflection of the consumer margin improving the ability of the model to explain entry and exit decisions. But this reduction in average entry costs, when introducing this consumer margin, is not only due to this smaller variance, but also characterizes an important change in the relative role played by entry and per-period costs: while the ratio between entry costs and per-period costs is between 5 to 10 in the restricted model, it is only 3 to 5 in the full model. This reflects the introduction of the consumer margin capturing an important amount of state dependence, reducing the role played by entry costs in explaining the hysteresis in the export decision. This result will be very important when looking at models' predictions in response to shocks. Estimating large entry costs to export implies that the option value of exporting is very large: the large average entry costs make entering so difficult that firms will hesitate to exit this export market. I will study these consequences in the next section when comparing the predictions of these models under simulated and observed trade shocks.

Another important difference between these two models emerges from the estimates of the cost of appeal. In the full model with consumer margin, appeal is very costly, making high-appeal products barely more profitable than low-appeal ones.[45] However, the model without consumer margin identifies product appeal with a low impact on prices, with an average estimate of 0.27. This difference is interesting because it describes how the introduction of consumer margin, affects the definition of appeal itself. When appeal is the unique demand shifter, it will capture the role of distribution network for instance and other characteristics that raise the sales of the firm conditional on prices. However, with the introduction of a consumer margin, part of this sales variation will be captured by this new margin, such that what the full model will infer as appeal will be more related to the type of good produced, and its characteristics. As a consequence, the appeal inferred in the full model is closer to what one could describe as product quality, which would explain its larger impact on the marginal costs of production.

1.5.3 Outcomes of the model

Finally, to conclude the description of the results, I discuss the evolution with export experience of two important objects introduced in this model: the consumer shares and the mark-up charged by firms. Figure 1.6 provides the distribution of consumer shares for each age of the firm. Remember that when firms enter, they all have an initial share $n_0 \approx 3\%$, which explains why the graphs provides distributions from ages 2 to 10. Figure 1.6 illustrates that the distribution tends to shift toward the right as age increases. One can see that most of the firms have a small consumer share at age 2: only a small fraction of them are larger than 25 percent. However, as age increases, more and more firms reach a larger size. Therefore, at age 10, a significant number of them has a consumer share that is larger than 50 percent. However, there is still a large amount of heterogeneity across ages. Some firms are large at ages 2 or 3, but a large fraction of them are still small in terms of consumer shares when reaching years 9 or 10. As a result, the overall distributions appear to flatten as age increases, rather than translate toward the left. This implies that the process of consumer accumulation is not identical across firms, and relies very much on the individual sales of the firm rather than an exogenous increase of consumers with age. Some firms will never reach a large

[45] In this model, appeal is exogenous and therefore could have a negative impact on sales and profit. This would be the case if $\alpha > \frac{1}{\sigma-1} \approx 0.83$.

fraction of consumers, because it is not profitable for them to do so.

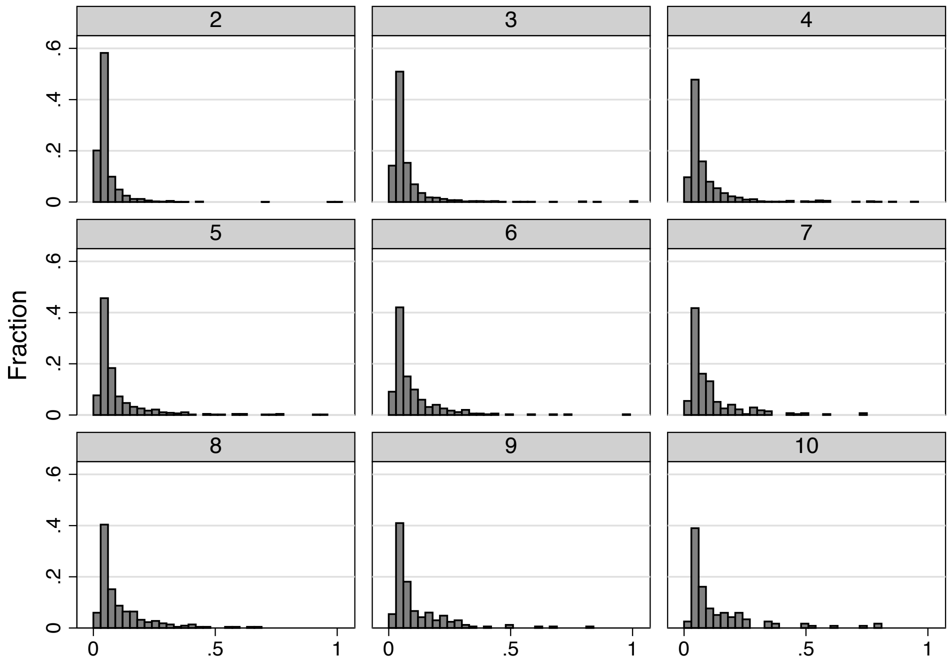

FIGURE 1.6: Distribution of consumer shares by age

After describing the evolution of the distribution of consumer shares, I turn to the distributions of the mark-ups charged by the firms. These mark-ups were the only tool for the firm to foster accumulation. Figure 1.7 reports the distributions of mark-ups, separately for each age from 1 to 9. Moreover, I report in red on these histograms, the CES mark-up in the absence of dynamic pricing ($\frac{\sigma}{\sigma-1}$): because of the dynamic benefits of charging low-markups, firms optimally charge a mark-up that is lower than the CES mark-up (as this is implied by the model). One can see that, similar to the consumer shares, there is a large heterogeneity in mark-ups across ages, but also within ages: the model does not imply a mechanical correlation between mark-ups and age. However, we can see that firms tend to price more aggressively at a young age, in comparison to more established firms. The reason is twofold: first, these firms are small and therefore benefit from large returns of higher sales on consumer accumulation. Second, because these firms are small and young, they are likely to not survive in the following years. Therefore, it is optimal to charge low prices because these new consumers increase their probability of survival: indeed, survival rates tend to increase, especially in the early years of exports. Finally, we can see that these dynamic incentives are so large, that some firms are willing to make negative profit during the current period, in order to invest in future consumers: a significant number of firms charge a mark-up that is lower than one, implying a price below marginal costs.

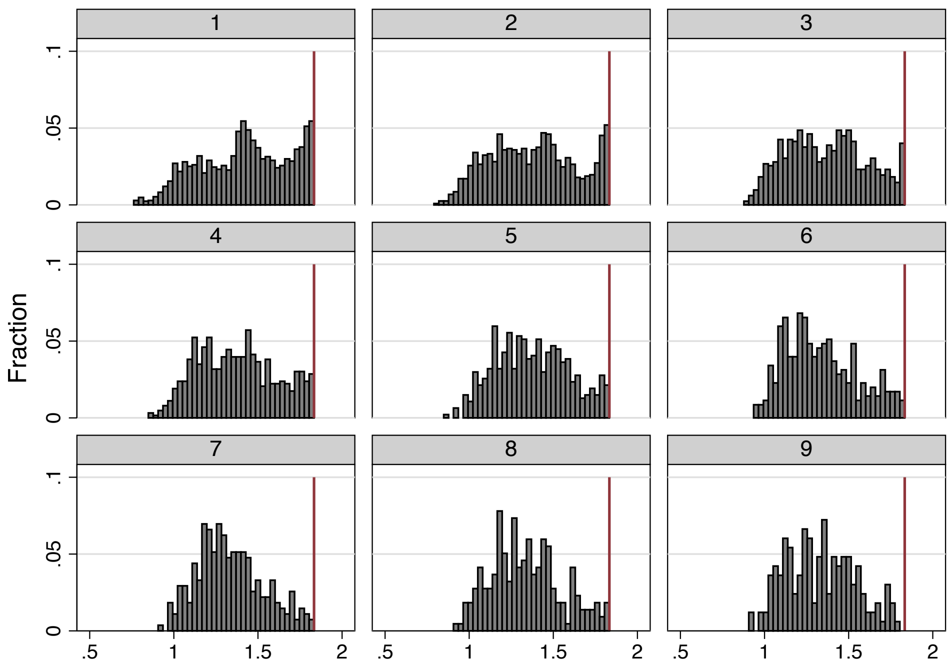

FIGURE 1.7: Distribution of mark-ups by age

1.6 Aggregate implications

In this section, I use simulations and out-of-sample predictions to demonstrate the importance of the model regarding the aggregate trade responses to shocks. The introduction of the consumer margin generates a sluggish response of trade flows, as it will take time for firms to reach new consumers. Moreover, low entry costs imply a stronger response of firms' entry and exit to shocks. As a consequence, the model can replicate two important facts regarding aggregate adjustments to trade shocks: first, in response to a positive trade shock, it will take time for aggregate trade to fully respond, generating a discrepancy between the short and long run trade elasticities. Second, the relative contribution of the extensive margin in this response will be increasing across time, as it has been recently documented in the literature. Finally, I directly test the performance of the model with an out-of-sample predictions exercise. I show that the model can better predict the actual trade response to exchange rate movements that took place during the sample period in the Brazilian market.

1.6.1 Sluggish trade response

The accumulation of consumers by the firms will generate frictions in growing on foreign markets. As a consequence, the trade response to shocks will be slow at the microeconomic and aggregate level. This pattern, which has been documented in the literature,[46] can explain the discrepancy that exists between the values of the trade elasticity at different horizons. International macro economists use elasticities around 1 or 2 in order to match trade responses to price variations at a high frequency. However, international trade economists use elasticities ranging from 6 to 8, in order to explain variations in trade flows across countries, or trade responses after a trade liberalization episode.[47]

In order to quantitatively evaluate the ability of the model to generate this discrepancy between horizons, I simulate a decrease of 10 points on the tariff applied to export from French firms to the US. I simulate the trajectories of the 200 firms from my sample following this tariff reduction, and compare them to a counterfactual scenario without tariff decrease. I apply this experiment to the full model, as well as the standard model that does not feature consumer accumulation. Figure 1.8 reports for each model, the log-deviation relative to the counterfactual scenario without tariff change, of the total trade to the US.

As we can see from figure 1.8, the predictions of the two models are significantly different. In the model without consumer margin, trade increases instantaneously as the shock occurs: with lower tariffs, exporters prices decrease and trade increase. Moreover, new exporters enter the market such that the trade response is larger than the only sales response to the price decrease. After these first years, no further adjustment occurs. In comparison, the model with consumer margin depicts a slower adjustment to trade as it takes up to 10 years to observe the full effect of the reduction

[46] See Alessandria et al. (2013) for instance

[47] See Ruhl (2008) that explains this international elasticity puzzle from the different impacts of permanent and temporary trade shocks.

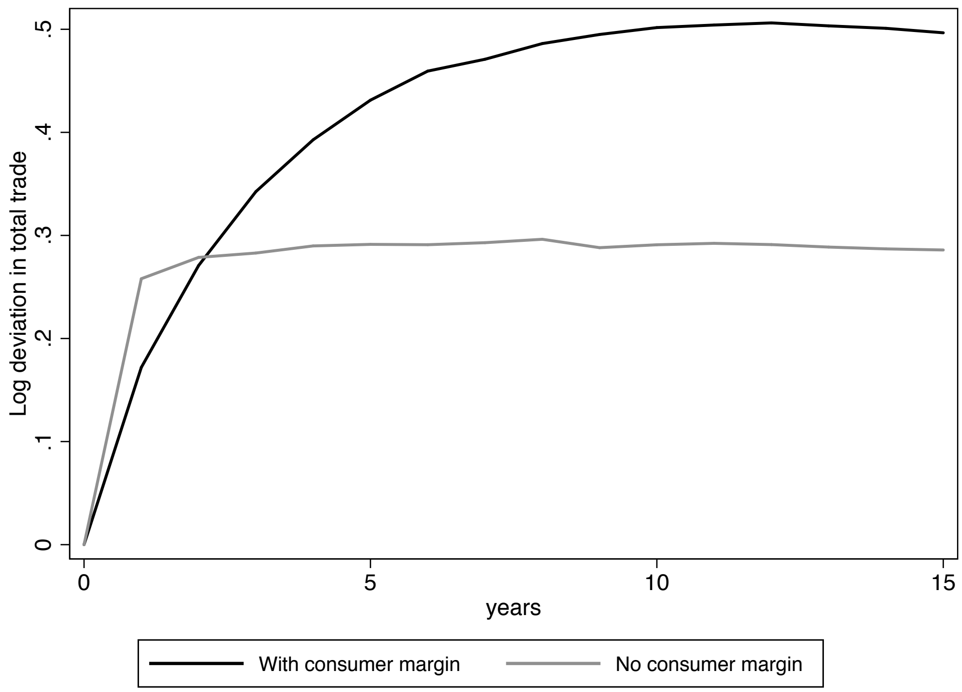

Figure 1.8: Effect of permanent 10 points tariffs decrease.

in tariff. The reason for this slow adjustment is that it takes time for existing and new exporters to reach their optimal number of consumers. As a consequence, we see a similar adjustment than the restricted model in the first year, because firms also benefit from lower prices, but this effect is magnified by the increase of the consumer shares of existing firms, as well as the entry of new firms that will grow in the subsequent years. Consequently, the full effect of the tariff reduction will be roughly 3 times the effect recorded after one year. Interestingly, this ratio between long-run and short-run elasticities is roughly consistent with the ratio of elasticities used in the two distinct literatures. As a conclusion, it appears that the model with consumer margin can generate this discrepancy, unlike the standard model that does not feature this margin.

1.6.2 Contribution of the extensive margin

A second implication of the model with consumer margin relates to the contribution of the extensive margin to the growth in trade throughout a trade liberalization episode. A number of recent papers documents the increasing contribution of new exporters or new goods at different time horizons: the contribution of the extensive margin is small right after a shock, but tend to increase in the following years to reach a significant contribution in the overall effect. For instance, Kehoe and Ruhl (2013) document this pattern for the contribution of new goods to the trade expansion following the North American Free Trade Agreement (NAFTA). Closer to my empirical application, Alessandria et al. (2013) provide similar evidence when looking at the extensive margin defined at the firm-destination level. In particular, they show that following a devaluation, the contribution of the extensive margin is almost zero in the first quarters after the shock, but can reach 50 percent of the total trade growth after 5 years.

I explore the predictions of my model, by decomposing the growth of trade following a decrease in tariff. I implement a tariff reduction similar to the previous section, and decompose the total growth in trade following the methodology by Hummels and Klenow (2005): this method allows the measurement of the contribution of each variable entering the demand function of the firm (intensive margin), and the contribution of new entrants (extensive margin). In this context, I am able to obtain 5 sources of growth: product appeal, consumer margin, prices, aggregate demand that constitute the intensive margin, and the extensive margin. In figure 1.9 I report the contribution of the aggregate demand (that captures the decrease in tariff), the consumer and the extensive margins along different time horizons.[48]

Figure 1.9 depicts the increasing contribution of the extensive margin. The first year after the shock, this contribution is very small, around 10 percent of a small increase in trade. However, as the horizon increases, this contribution is significantly larger, to reach up to 32 percent of the total growth in trade.[49] There are two important reasons to explain this increasing contribution. First, because of small entry costs, the response of the extensive margin is large: a small decrease in tariff leads to significant entry of new firms on the export market. However, even though the number of these entrants is large, these exporters enter very small, and therefore do no contribute very much to aggregate trade. But as they survive on the market, and increase their stock of consumers, they become large exporters and significantly contribute to the growth in trade triggered by the tariff reduction. Moreover, due to the concavity of the consumer accumulation technology, these new entrants will grow faster than experienced firms, hence increasing their relative contribution across years. We can see that the contribution at the end of the period is around 30 percent, which is

[48]The other margins being insignificant, I choose to not report them for clarity. The decomposition between all the margins are displayed in figure A.8 in appendix A.4.

[49]See figure A.9 in appendix A.4 for the relative contribution of each of these margins across time.

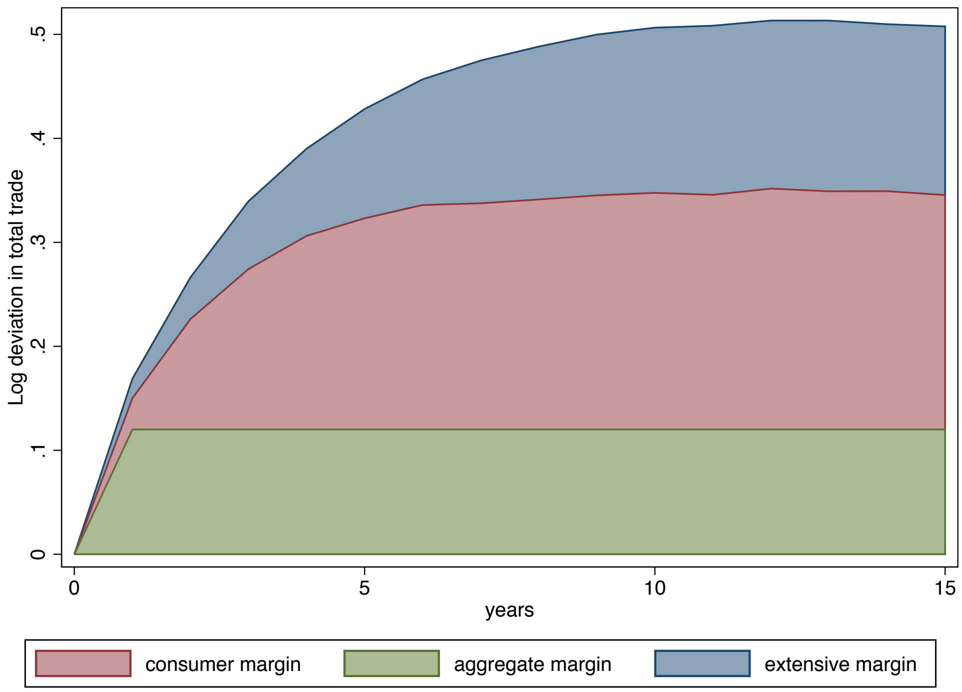

FIGURE 1.9: Effect of permanent 10 points tariffs decrease.

roughly consistent with the numbers provided in Alessandria et al. (2013).[50] In comparison, the model without consumer margin does not feature this growth in the contribution of the extensive margin.[51]

1.6.3 Out-of-sample predictions: export response to exchange rate variations in Brazil.

In order to further demonstrate the relevance of the model with consumer margin, I compare its predictions relative to the standard model in an out-of-sample predictions exercise. Because I study the export decisions on a limited set of destinations, I can take advantage of additional destinations, that have not been previously used in the estimation, to test the ability of the model to correctly predict the exporting behavior of the French exporters contained in my sample. In particular, I want to perform this exercise in a market that has recorded important and measurable trade shocks. This will allow me to feed this shock into the model, and compare the predicted response of both

[50] They report a contribution of the extensive margin of 30 and 60 percent after 5 years, respectively in Uruguay and Mexico.

[51] See figure A.10 in appendix A.4 for the prediction using the restricted version of the model.

models to the actual behaviors of exporters.

I apply this methodology to the Brazilian wine market during my sample period.[52] The choice of the Brazilian market is based on two reasons: first, it is a large market such that a large enough number of French wine producers export to Brazil. Second, the Brazilian wine market has recorded during the sample period two important shocks that affected the Brazilian demand for French wine. The first one is the devaluation of the Brazilian currency, the real, in 1999, that has been followed by a strong depreciation of the currency in the following years, and an appreciation starting 2003. This depreciation generated a strong increase in the price of French wines in local currency. The second large shock arises from the Argentinian devaluation that took place in 2002. After the abandon of the peso-dollar parity, the Argentinian currency recorded a strong depreciation that led to a strong growth in wine export to Brazil. As a close neighbor and a massive wine producer, this decrease in Argentinian prices caused an important drop of the price index on the Brazilian wine market.

Therefore, I take advantage of these variations in exchange rates, which can be arguably seen as exogenous to French exporters behavior, as sources of variation in the aggregate demand received by French firms. The model relies on five state variables that characterize the entry and sales of exporters: the appeal λ_{ft} and productivity ϕ_{ft} of the firms, their consumer shares n_{fdt}, the aggregate demand from a destination X_{dt} and their previous export activity $\mathcal{I}_{fdt-1}$. Because the quality and productivity of the firms are common across destinations, I can use the estimated individual qualities and productivities from the estimation procedure. Moreover, the variables n_{fdt} and $\mathcal{I}_{fdt-1}$ will be obtained from the predictions of the model, such that only initial conditions are required for these variables. Therefore, with the variable X_{dt} that describes the aggregate demand from Brazil, the model is able to deliver predictions of entry, sales and prices on the Brazilian market for each of the 200 firms I used in the estimation.

I will construct this variable X_{dt} for Brazil by using variations in real exchange rates and the Brazilian GDP. From the demand equation used in the model, X_{dt} is defined as:

$$X_{dt} = \log Y_{dt} - (1-\sigma) \log P_{dt} + (1-\sigma) \log(\tau_{dt} e_{dt})$$

in which Y_{dt} is the amount spent by Brazilian consumers in wine, P_{dt} is the price index for wine

[52] My sample period goes from 1997 to 2010. However, I will stop my predictions in 2007, since the great trade collapse generated a strong decrease in trade that is difficult to account for in the model.

TABLE 1.4: Top market shares

Country	Average market share
France	22.1 %
Italy	20.4 %
Chile	19.6 %
Argentina	13.5 %

Notes: Calculations made from BACI. Average market share is the average market share among the Brazilian imports, over the period 1997-2007, for the 4-digit category 2204 '*Wine of fresh grapes*'.

in Brazil, and τ_{dt} and e_{dt} are transportation costs and exchange rates between French exporters and Brazilian consumers. Therefore, I will proxy variations in $\log Y_{dt}$ by variations in the log GDP of Brazil, and variations in $\log(\tau_{dt} e_{dt})$ using variations in the BRA/FRA exchange rates. Finally, to construct a proxy for the price index, I will use the variations in exchange rates of the main exporters to Brazil as featured in table 1.4.[53] Based on these data, I can construct variations in $X_{BRA,t}$ from 1997 to 2007.[54] To obtain the values in level of $X_{BRA,t}$, I will set $X_{BRA,t}$ such that the sales of the median prediction equals the realized sales on the market during the year before the shock, 1998. Therefore, the focus of the exercise will be on variations in sales and entry after this year.

The results of these predictions are displayed in figure 1.10 for the total trade, and figure 1.11 for the number of exporters. These figures display the realized data, as well as the predictions from the full model with consumer margin and the standard model without consumer margin. Moreover, I report confidence intervals at 90 percent: each prediction still requires the simulations of the shocks ε and ν, to infer entry, sales and pricing behaviors, which explains the variability in the predictions.[55] Figure 1.10 reports the strong decrease in wine export to Brazil that occurs between 1998 to 2003. This decrease is explained by the Brazilian devaluation in 1999, and the growth in Argentinian export led by their devaluation in 2002. However, total exports increase after 2003 as a result of the improvement in economic conditions in Brazil at this period. Regarding the predictions of the models, we can see that the model without consumer margin does not react very much to the

[53] These four countries account for 75 percent of the total wine import of Brazil. The fifth exporter (Portugal) has a market share of less than 2 percent and therefore is not included in the construction of the price index.

[54] The obtained variations in $X_{BRA,t}$ are displayed in figure A.11 in appendix A.4

[55] For each model, I simulate 500 samples of these shocks, leading to 500 different predictions. I report the median prediction as well as the 5th and 95th percentiles in the figures.

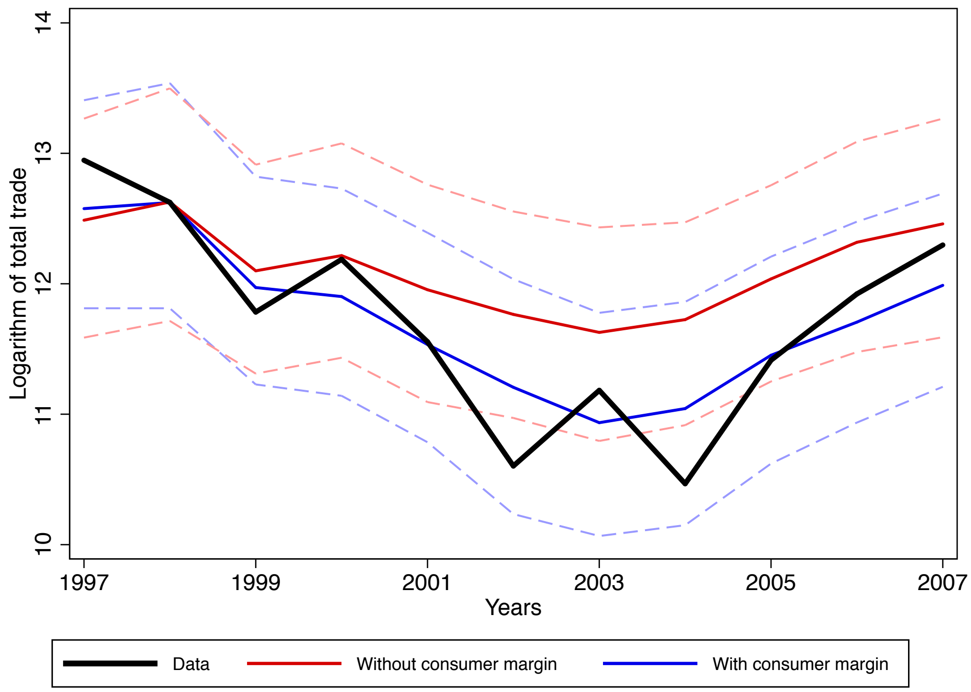

FIGURE 1.10: Total exports of wine to Brazil from selected firms

changes in exchange rates. This variation in relative prices does reduce sales, but not in the same magnitude as in the data. However, the model with consumer margin can predict the large drop in trade, as well as the rebound starting in 2004. This difference in trade predictions arises because the number of exporters reacts minimally to exchange rates in the model without consumer margin.

Figure 1.11 reports the prediction of the number of exporters in the two models. The model with consumer margin, unlike the restricted model, can reproduce the decrease in the number of exporters in 1999 and 2002. This decrease is the reason for the larger variation in total trade shown in the previous figure. However, in the model without consumer accumulation, the large entry costs of exporting cause the non exit of exporters: the option value of the exporting activity is so large that no exporters will exit as it will be very hard to reenter in the future. They are willing to lose money temporarily, in order to keep the option value of exporting in the next years. However, in the model with consumer margin and low entry costs, firms are willing to leave the market as the economic condition deteriorates. For similar reasons, as the perspectives on the market improve after 2003, we observe a larger growth rate of the number of exporters in the model with consumer margin. However, both models tend to strongly overpredict the number of exporters in the early

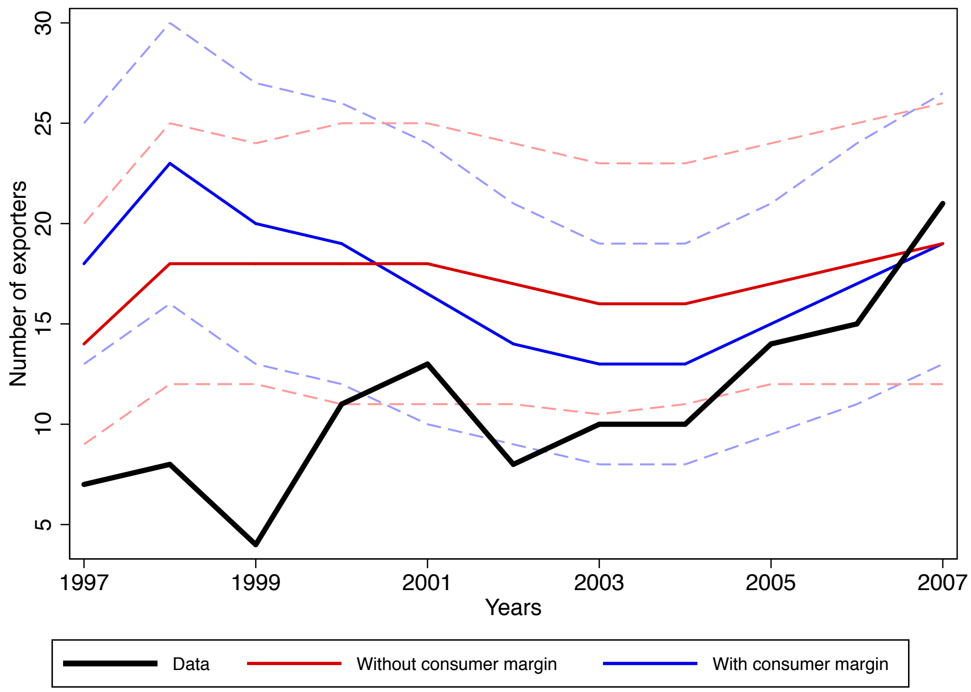

Figure 1.11: Number of wine exporters to Brazil from selected firms

years of the sample period. Two possible reasons could explain this overprediction. First, the model does not account for specific expectations of exporters. Because the law of motion of the aggregate demand term is similar across destinations, the model does not capture the likely low expectations regarding the Brazilian market before the devaluation. Second, part of this overprediction arises from the random nature of the sampling of firms. When looking at aggregate data of the variations in the number of French wine exporters to Brazil, these variations look similar to the observed variations in total trade displayed in figure 1.10, and to the predictions of the model.

Overall, it appears that the predictions of the model with consumer margin, unlike the standard model, can quantitatively replicate the decrease in total trade during this period. This result mostly comes from the larger response of firms entry and exit, due to the lower level of the entry costs of exporting in this model.

1.7 Conclusion

In this paper, I develop and estimate a dynamic empirical model of trade that features state dependence in demand through the accumulation of consumers in foreign markets. Estimating the model using a set of French wine exporters, I show that accounting for this dependence is critical to understand the entry and exit decisions of firms in foreign markets, but also for the estimation of the costs of exporting: on average, estimated entry costs are a third of those estimated in the standard model without consumer accumulation. Moreover, I demonstrate using simulations and out-of-sample predictions that this consumer margin, and the associated fall in entry costs, matters for aggregate predictions. First, I show that this model can generate a slow response of aggregate trade to shocks. The trade elasticity in the long run is three times larger than the short run, which is consistent with patterns documented in the literature. Second, the model can correctly replicate the contribution of the extensive margin throughout a trade liberalization episode.

These results shed new light on the nature of the barriers to trade at the firm level. While existing models emphasize the role of large sunk entry costs as the main barrier to trade to explain the persistence in export markets, this paper shows that dependence in demand is responsible for a significant share of this persistence. In fact, the ability to reach a large and stable demand for a product appears to be one of the primary sources of success for firms in foreign markets. Therefore, this study improves our understanding of the determinants of trade dynamics at the microeconomic and aggregate levels. This result has important policy implications for countries designing policies to improve the export performance of their industries.

Chapter 2

Estimating firm-level product quality using trade data

Paul Piveteau and Gabriel Smagghue[1]

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2.1 Introduction

Trade economists have long investigated the role played by product quality in shaping the pattern of trade at the macroeconomic level.[2] A more recent literature has emphasized the importance of product quality at the microeconomic level: in addition to being one of the main sources of firm heterogeneity,[3] the quality supplied by firms impacts the relative demand for inputs, which makes it decisive to understand the link between globalization and inequalities.[4] These findings came with a growing demand from trade economists for disaggregated data on product quality. In spite of that, estimating firm-level quality on trade data remains an empirical challenge as traditional techniques developed in Industrial Organization cannot be applied to datasets in which product characteristics are not observed,[5] which is typically the case with international trade data.[6]

In this paper, we propose and implement a new empirical methodology to estimate product quality at the firm level. We create a new instrument for prices, based on exchange rate variations interacted with firm-specific importing shares, that allows us to consistently estimate demand equations in the absence of observable product characteristics. Implementing this methodology using customs data from France, we first document the reliability of our estimation, by comparing the obtained measure of quality with alternative measures of quality and with other firm characteristics. Then, we take advantage of these new measures to document the quality response of French exporters to competition from low-cost countries.

The first contribution of this paper is to provide a new method to estimate quality using trade data. We estimate quality from the demand side. The main challenge one faces when estimating demand functions is to deal with the endogeneity of prices: prices are likely to be correlated to demand shocks, because quality is costly to produce.[7] Consequently, researchers have used unit values or prices as proxies for quality, or have estimated demand equations in contexts where

[2] The oldest theory of product quality in international trade goes back to Linder (1961).

[3] See Roberts, Xu, Fan, and Zhang (2012) and Hottman, Redding, and Weinstein (2016) for empirical quantifications of the relative importance of different sources of heterogeneity at the firm level.

[4] Verhoogen (2008) and Brambilla et al. (2012) document the consequences of trade openness on wage inequality.

[5] Industrial Organization has developed strategies to back out quality by estimating a demand equation. In this approach, the presence of omitted product characteristics challenges the identification as these characteristics are likely to be correlated with the price of the product which induces an endogeneity bias.

[6] Exceptions include Crozet et al. (2012) and Garcia-Marin (2014) who use expert ratings of quality of Champagne and wine, as quality measures.

[7] See, e.g., Hallak and Sivadasan (2013), Johnson (2012) and Kugler and Verhoogen (2012) for trade models where quality is costly and endogenous at the firm-level.

unobserved vertical differentiation is limited.[8] To address this endogeneity issue, we construct a novel instrument for prices, exploiting fluctuations in exchange rates. These fluctuations, interacted with firm-specific import shares, shift a firm's costs of importing goods. As the firm passes importing cost variations on to its consumers, the instrument generates firm-specific export price and sales variations. These variations are arguably exogenous to unobserved demand shocks (e.g., quality shocks) and allow us to identify the price-elasticity of exports.[9] Quality is then identified at the firm, destination, product, year level, from the residual variations of demand once price variations have been controlled for; a strategy that is present throughout the literature.

The implementation of this method using customs data from France, supports the validity of the procedure. First, we find that the import-weighted exchange rate, our instrument, is strongly and positively correlated to export prices charged by firms. This is consistent with the assumption we make to motivate the instrumentation, namely that exchange rates shift a firm's production costs. Second, in order to evaluate the ability of our instrument to correct for the endogeneity of prices, we estimate the demand equation both via ordinary least squares and two stages least squares. Our instrumental variable procedure affects the estimates of price-elasticities consistently with a correction of an omitted variable bias: while ordinary least squares estimates deliver a low (in absolute value) price-elasticity (0.8), the instrumental variable approach produces estimates consistent with the existing studies in the industrial organization literature, ranging from 1.8 to 2.4, depending on the specification. In order to further assess the reasonableness of our price elasticity estimates, we rely on cross-industry comparisons. In line with evidence at the country-product level, we find that demand is significantly more elastic in more homogeneous sectors.[10] Finally, we investigate the properties of our quality estimates by running correlations with existing measures of quality at the firm-level. A natural benchmark is provided by Crozet et al. (2012) who use one of the very few "direct" measure of firm-specific quality present in the literature, by relying on ratings attributed by an expert to a sample of French Champagne producers. We compare

[8] Broda and Weinstein (2010) and Handbury (2012) use barcode-level data, that features no quality variation within barcode across time, whereas Foster, Haltiwanger, and Syverson (2008) restrict their analysis to homogeneous products.

[9] The use of exchange rates as an instrument for prices connects our estimation to Berman et al. (2012) and Amiti et al. (2014). These studies empirically analyze the firm-level pass-through from exchange rates to export prices. However while both works are interested in the heterogeneity of the pass-through across firms, we only use the effect of exchange rates on export prices as a first stage to a demand function estimation.

[10] See Broda and Weinstein (2006).

these ratings with our estimated quality of exported Champagne and find a positive and strongly significant correlation. Moreover, prices, the most popular proxy for quality in the literature, are also positively and significantly correlated to quality, both in the cross-section of firms, as well as over time within a firm. However, this correlation is significantly smaller for more homogeneous sectors: using Sutton (2001)'s sectoral measure of vertical differentiation, we find that in the least vertically differentiated product category, prices are approximately 3 times less elastic to quality than in the most differentiated product category. In other words, prices are informative on quality, but less so in more homogeneous sectors.

A second contribution of this paper is to exploit these new quality estimates to document the quality response of French firms to low-cost competition. The recent increase in the participation of low-wage countries in international trade has had a large impact on manufacturing industries in developed economies. In this context, firms from developed countries may choose to innovate and to upgrade the quality of their products as a way to escape competition.[11] Our quality estimation is especially relevant in this context as it allows us to look at the change in quality across time within firms, in response to low-wage competition. Our identification strategy consists in correlating the dynamics of low-cost competition in foreign markets with the dynamics of the product quality supplied by French firms to these markets. In order to obtain variations in low-cost competition across firms within a similar market, we first compute the penetration of low-wage countries at the country-product-year level using the trade dataset BACI. Then, for each destination market and each firm, we construct a measure of the low-cost competition faced by the firm in the rest of the world. This measure varies across firms within a market since firms serve different destinations. We identify the quality response to competition from the firm-specific dynamics in this rest-of-the-world measure of competition. This identification strategy assumes that there is a positive correlation in the quality of a good supplied by a firm across destinations. Intuitively, we assume that within the firm, the quality adjustment due to competition in one destination spills over the quality served to other destinations.

Using this identification strategy, our results suggest that low-cost competition induces quality upgrading within the firm. Interestingly, the response of quality takes time to occur. More specifically, the quality of a firm raises by 2% four years after a 10 percentage point increase of the

[11] See Bloom et al. (2013) for a model of innovation in which higher competition fosters innovation within the firm.

low-wage countries' penetration rate. We find no significant response before three years. It suggests that upgrading quality requires slow adjustments within the firm. In addition, we find that quality upgrading is more pronounced in more vertically differentiated industries. These results contribute to the literature on the relationship between firm-level quality and trade exposure. While existing studies mostly focus on firms from developing countries (see, e.g., Verhoogen 2008; Brambilla et al. 2012; Khandelwal et al. 2013), our results suggest a new channel through which firms from developed countries can mitigate the impact from low-wage competition.

This paper is directly related to the literature aiming to measure quality using trade data. Most of the literature back up quality measures from the estimation of a demand system, following the tradition in Industrial Organization.[12] In particular, we can cite Hallak and Schott (2011) and Khandelwal (2010) who rely on an instrumental variable approach to identify quality at the country-product level using trade data. To be applied at the firm-product level, their methods require an instrument for prices which varies across firms. We provide such an instrument. Gervais (2015) and Roberts et al. (2012) also estimate quality at the firm level by instrumenting prices. However, these studies use instruments, respectively physical productivity and wages, which are questionable if quality varies over time, within the firm. By contrast, our instrument is robust to time-varying quality. Because of the difficulty of estimating demand equations at the firm level, in the absence of product characteristics, researchers have relied on alternative strategies: Khandelwal et al. (2013) construct quality by calibrating price-elasticity with estimates from Broda and Weinstein (2006). The relevancy of these price-elasticities estimates is open to question as they are obtained from country-level data. Alternatively, demand equations have been estimated in contexts where unobserved vertical differentiation is limited: for instance, Broda and Weinstein (2010) and Handbury (2012) use barcode-level data, whereas Foster, Haltiwanger, and Syverson (2008) restrict their analysis to homogeneous products. Finally, as mentioned earlier, a number of papers have used prices as proxy for quality: we can cite for instance Kugler and Verhoogen (2012) and Manova and Zhang (2012) that document quality variations across firms, and within firm across destinations

[12]Most notable contributions in IO include Berry, Levinsohn, and Pakes (1995) and Berry (1994). These papers have contributed to the estimation of structural demand parameters by introducing demand systems exhibiting more sophisticated substitution patterns. However, the structure included in these papers does not solve the issue that prices are endogenous to quality in the demand equation. Therefore, these structural empirical models do not dispense from finding an instrument for prices, but can usually rely on product characteristics that control for mosts of the variation in quality across goods.

using firm-level or customs data that features prices of good produced by firms.

Finally, our work is related to papers measuring the impact of competition from low-cost countries on developed economies. Autor et al. (2013) show how manufacturing workers in the United States have been hurt by the increasing penetration of Chinese goods on the American market. Relatedly, Khandelwal (2010) provides evidence that the impact of low-wage competition has been significantly larger in industries with shorter quality ladders. Closer to our question, Martin and Mejean (2014) show that low-cost competition induces a reallocation of market shares towards higher quality firms which ultimately results in a rise of aggregate quality. Moreover, Bloom et al. (2016) document that firms facing higher levels of competition from low-cost countries increase their effort in innovation. We position our paper at the intersection of two previous papers by documenting a within-firm response to low-wage competition, using a direct measure of quality.

This paper is structured as follows. In the next section, we derive a simple model of demand with vertically-differentiated goods. In section 2.3, we present our novel instrumental strategy, implement it using French customs data and demonstrate its effectiveness. In section 2.4, we describe the quality estimates we obtain through correlations to alternative measures. In section 2.5, we investigate the impact of low-cost competition on within-firm quality adjustments. Finally, section 2.6 concludes.

2.2 Quality Estimation Strategy

In this section, we present a novel strategy to estimate the quality of exports at the firm-product-destination-year level, using customs data. Since we identify quality from the demand side, we start this presentation by describing the demand system that we consider. In this demand system, quality acts as a demand shifter. This implies that variations in the quality of exported goods over time and across firms will be revealed from variations in sales controlling for prices.

In order to identify the demand system and pick up quality, we then present a novel instrument for the price of firms' exports. This instrument is obtained by interacting firm-specific importing shares with real exchange rates. We make explicit the conditions of validity of this instrument and explain why alternative instruments in the literature would not be valid in the context of this paper.

2.2.1 An Empirical Model of Demand for Quality

Let us consider a global economy composed of a collection of destination markets d. In each market, the representative consumer allocates its revenue over the different varieties of each product g. Our definition of product categories follows the structure of French customs data. Namely, a product corresponds to a 8 digit position of the Combined Nomenclature (CN). A variety is defined as a unique combination of a destination market d, a producing firm f and a product g. Producing firms are located in different countries. Hereafter we call "home" the country for which firm-level export data are available to the econometrician (Home is France in the application) and we note $\mathcal{H}_{gdt}$ the set of firms exporting good g from home to country d at year t.

Representative consumers have two tier preferences. The lower level of the utility function aggregates consumptions of varieties by product. The upper level aggregates consumptions across products. We assume that the lower part of the utility function is CES while we do not impose any functional form on the upper level. It follows that an expression of the utility of representative consumer in market d at year t is

$$\begin{aligned} U_{dt} &= U\left(C_{1dt}, .., C_{Gdt}\right), \\ C_{gdt} &= \left[\sum_{f \in \Omega_{gdt}} \left(q_{fgdt}\, x_{fgdt}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \qquad \forall\, g = 1..G, \end{aligned} \tag{2.1}$$

with $U(.)$ a well-behaved utility function, C_{gdt} the CES aggregate consumption of good g in destination d at year t, Ω_{gdt} the set of varieties of good g available to consumers, σ the elasticity of substitution across varieties within a good and x_{fgdt} and q_{fgdt} respectively the aggregate physical consumption and the quality of variety fgd at year t.[13]

Utility function (2.1) imposes no restriction on the patterns of substitutability across goods.[14] Within goods, varieties are equally substitutable.[15] In equation (2.1), quality is modeled as a utility

[13] We assume an unique elasticity of subtitution to present the model, but will be able partially relax this assumption across industries in the empirical application.

[14] However, the nested structure of the utility function imposes that all varieties of a good are equally substitutable to the varieties of another good. This means for instance that Peugeot cars may be a substitute or a complement to Nike T-shirts. But provided that they are, say, substitutes, then any combination of a car variety and a T-shirt variety are also substitutes.

[15] This feature is shared by most estimations of demand systems with vertically differentiated goods based on aggregate data. In the nested logit specification of Khandelwal (2010), for instance, the elasticity of substitution is the same for any two varieties within a nest, irrespective of their quality. This feature also appears in the random effect logit model of Berry et al. (1995) where the utility shifter ξ (the analogue of our quality q) is not multiplied by

shifter, i.e. a number of units of utility per physical unit of good. This implicitly defines quality as an index containing any characteristic of a variety which raises consumers' valuation of it. These characteristics may be tangible (e.g. size, color) as well as intangible (e.g. reputation, quality of the customer service, brand name). This broad definition is consistent with most of the literature in international trade and quality.[16]

The representative consumer allocates its total expenditure, E_{dt}, across goods and varieties, in order to maximize its utility (2.1). This behavior results in the following aggregate residual demand function for variety fgd:

$$r_{fgdt} = {p^*_{fgdt}}^{1-\sigma} q^{\sigma-1}_{fgdt} P^{\sigma-1}_{gdt} E_{gdt}, \tag{2.2}$$

with r_{fgdt} the sales of variety fgd in value and E_{gdt} the expenditure optimally allocated to good g. p^*_{fgdt} is the price of variety fgd faced by consumers of market m. Namely, p^*_{fgdt} is the CIF (Cost Insurance Freight) price labeled in market d's currency. P_{gdt} is the price index of good g in market d at year t.[17]

In order to properly grasp the properties of demand function (2.2), it is worth noting that $-\sigma$ is not the own price elasticity of variety fgd's demand. It is the own price elasticity *keeping constant the price index* P_{gdt} *and the aggregate expenditure* E_{gdt}. In a monopolistic competition setting, firms are atomistic and their individual decisions do not influence these aggregate variables. However, with non-atomistic firms, the own price elasticity may differ from $-\sigma$ and be heterogeneous across firms.[18]

We assume that exporting involves iceberg trade costs. In particular, domestic firms need to

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a random coefficient.

[16]Because of the wide range of product attributes potentially captured by our concept of "quality", some papers have adopted a more conservative terminology. For instance, Roberts et al. (2012) refer to the variety-specific utility shifter as a "demand index", Foster et al. (2008) to "demand fundamental" and Hottman et al. (2016) to "product appeal".

[17]The price index verifies:

$$P_{gdt} = \left(\sum_{f \in \Omega_{gdt}} \left(\frac{p^*_{fgdt}}{q_{fgdt}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

[18]This point is made simple by observing that our framework nests a quality-version of Atkeson and Burstein (2008). This corresponds to the special case where the upper tier utility function $U(.)$ is CES with an elasticity of substitution $\eta < \sigma$, and firms compete a la Cournot. Atkeson and Burstein (2008) show that in that configuration, firm own price elasticity tends to σ when their market share tends to zero while it tends to η when their nest-specific market share tends to one.

ship $\tau_{gdt} \geq 1$ units of good g for one unit to reach the consumer in market d at year t. So for varieties exported from home to market d, the CIF price in d currency (p^*_{fgdt}) is linked to the FOB (Free on Board) price in home currency (p_{fgdt}) by following relationship:

$$p^*_{fgdt} = \frac{\tau_{dt}}{e_{dt}} p_{fgdt}, \tag{2.3}$$

with e_{dt} the direct nominal exchange rate from home currency (Euro in the application) to market d's, i.e. that one unit of d currency buys e_{dt} units of home currency. Plugging (2.3) and log-linearizing, we can re-express demand function (2.2) for domestic firms as follows:

$$\log r_{fgdt} = (1-\sigma)\log p_{fgdt} + \lambda_{fgdt} + \mu_{gdt} \tag{2.4}$$
$$\text{with} \quad \begin{cases} \lambda_{fgdt} \equiv (\sigma-1)\left(\log q_{fgdt} - \overline{\log q}_{gdt}\right) \\ \mu_{gdt} \equiv \log\left(\frac{\tau_{gdt}}{e_{gdt}}\right)^{1-\sigma} + \log P_{gdt} + \log E_{gdt} + (\sigma-1)\overline{\log q}_{gdt} \end{cases}$$

and $\overline{\log q}_{gdt} \equiv \frac{1}{\mathcal{H}_{gdt}} \sum_{f\in\mathcal{H}_{gdt}} \log q_{fgdt}$ the average log-quality of good g supplied by domestic firms to market d at year t.

Equation (2.4) is the one that we bring to the data. In (2.4), $\log r_{fgdt}$ and $\log p_{fgdt}$ are observable to the econometrician while $(1-\sigma)$, λ_{fgdt} and μ_{gdt} have to be estimated. One can see from (2.4) that the demand shifter of a firm contains a variety-specific as well as a nest-specific term (respectively λ_{fgdt} and μ_{gdt}). The latter term will be estimated by including a destination-product-year fixed effect in the regression. This term is not informative on quality as it conflates the average quality of domestic exports with other aggregate variables. Thus, the estimation developed in this paper identifies quality from λ_{fgdt}, the variety-specific part of the demand shifter. Incidentally, the presence of quality in the demand shifter also causes the potential endogeneity of prices as we discuss further below.

From the structural expression of λ_{fgdt} in (2.4), one can see that our strategy does not deliver an absolute measure of quality. Instead we obtain a measure of quality which is relative to the average quality supplied by domestic firms to a market. A corollary is that λ_{fgdt} will not be suited to analyze variations in the aggregate quality of home exports, but rather how firms move relative to each other along the quality ladder across markets and over time. Moreover, because we assume that all firms will have the same elasticity, and therefore mark-ups, within a category, any deviation from this markup will be attributed to our quality measure. Therefore, this quality measure will also capture the additional market power that some firms have, allowing them to receive a demand less elastic to their price.

As a final remark on the demand system, it is interesting to note that a discrete choice model with nested-logit preferences a la Khandelwal (2010) would also deliver an aggregate demand function (2.4). The exact structural interpretation of parameters $1-\sigma$, μ_{gdt}, λ_{fgdt} slightly changes in the nested-logit set-up. However, our parameter of interest, λ_{fgdt}, is still a measure of relative quality across domestic firms serving a same good to a same destination. This is an important point as it implies that our quality estimation is robust to relaxing the representative consumer assumption.[19]

The next subsection describes the estimation of demand function (2.4) with a focus on our treatment of the endogeneity of prices.

2.2.2 Dealing with Price Endogeneity

In our setup, the endogeneity of prices comes from two mechanisms. First, we face a well-known simultaneity problem as prices are likely to be correlated to quality which is in the residual of the demand function. Assuming that high quality varieties are more costly to produce, this correlation would result from firms passing on the cost of quality to consumers. This endogeneity channel leads ordinary least squares to underestimate the price-elasticity of demand, σ. Indeed, when a firm increases the quality of its products, the effect of prices on demand is compensated with the greater appeal of the good to consumers.

A second source of endogeneity, more specific to international trade data, comes from the construction of prices. Because prices are not directly observed, we follow the standard practice and use unit values as a proxy for prices. Unit values are obtained by dividing the value of a shipment by the physical quantity shipped. The use of this proxy may generate an attenuation bias due to the measurement error contained in the price variable.[20]

[19] This similarity between our demand system and the nested-logit system echoes Anderson et al. (1987) who show that a discrete choice model with heterogeneous consumers may deliver a CES demand system at the aggregate level.

[20] This attenuation bias will certainly be magnified by the flow fixed effects we use in our estimation. In fact, in the time series of a trade flow, the measurement error may represent a larger share of the variation of unit values than in the cross-section.

Existing Methods Existing literature has used different empirical strategies to deal with price endogeneity. In particular, the literature in Industrial Organization has developed estimation procedures with instruments for prices. For instance, Berry et al. (1995) use competitors' product characteristics, Hausman (1996) and Nevo (2000) use product's price on other markets, while Foster et al. (2008) rely on estimated physical productivities. However, these instruments are not valid in the presence of *unobserved* vertical differentiation.[21] As a consequence, these instruments are not usable in our context. Indeed, trade data contain no product characteristic, except for the category in the product classification. Despite a narrow definition of these categories (8-digit CN classification present in our data has around 8,000 positions), there is still a wide scope for (unobserved) vertical differentiation within each category.

Some strategies for demand estimation with trade data exist at the country level. Khandelwal (2010) and Hallak and Schott (2011) use IV approaches. Their strategy are not suited to firm-level demand estimation as their instruments vary at the market level, not across firms within a market. Feenstra (1994) and Broda and Weinstein (2010) respectively develop and refine a very influential demand estimation using country-level trade data. Their identification exploits the heteroskedasticity of supply and demand shocks. Although there strategy could be applied to firm-level trade data, it involves an orthogonality assumption between demand and supply shocks which is likely to be violated in the presence of vertical differentiation (e.g., if quality is costly).

Literature on demand estimation with trade data is scarcer at the firm-level. Roberts et al. (2012) and Gervais (2015) use firms' wages and physical productivities as instruments for prices. These instruments are only valid if product quality is constant over time within the firm. For instance, if a firm upgrades its quality, it might need more workers per physical unit of output. In that case physical productivity is (negatively) correlated to quality and OLS estimate of σ is biased downward. The assumption that product quality is time-invariant is not sustainable in the present paper as our goal is precisely to identify within-firm quality variations induced by low-wage countries competition. Khandelwal et al. (2013) construct a firm-level quality measure by calibrating a CES demand system with price-elasticity estimates from Broda and Weinstein (2006). Conceptually,

[21] Berry et al. (1995), Hausman (1996) and Nevo (2000) all study specific markets, for which they clearly observe different varieties of a good, as well as their characteristics, reducing the possibility for unobserved quality differences. In a different setup, Foster et al. (2008) and Handbury (2012) estimate demand functions for a wide range of products, but either restrict their analysis to homogeneous products or use barcode-level data, which rule out the possibility of unobserved quality differences.

this approach raises two concerns. First, it implicitly inherits the identifying assumptions from Broda and Weinstein (2006). We explained above that these assumptions are problematic in the presence of vertical differentiation. Second, Broda and Weinstein (2006) estimates are obtained from country-level data. Elasticity may differ at the micro and the macro level,[22] which would generate biases in estimated firm-level quality.

Because existing methods do not lend themselves to our exercise, we develop a new instrumental strategy, robust to unobserved and time-varying quality differences within product categories.

A Novel Instrument for Prices at the Firm-level The approach developed in this paper takes advantage of the information coming from the importing activity of exporters. We use real exchange rates fluctuations faced by importing firms to instrument prices of exported goods. The basic idea is that real exchange rate shocks on a firm's imports are cost shocks. As the firm passes these cost shocks through to its export prices, sales adjust and the demand function is identified. Appendix B.1 formalizes this mechanism. In order to generate firm-specific exchange rate shocks, we take advantage of the fact that the spatial structure of imports varies across firms

To gain insight into the identification, let us study the example of two firms selling in a same market. One firm imports from the United States, while the other imports from Europe. An appreciation of the dollar would induce an increase of the export price of the former, leaving unchanged the price of the latter. The response of these firms' relative sales to the change in their relative prices identifies the price-elasticity of demand. This example also conveys the intuition of our main identifying assumption: relative real exchange rate shocks across firms should be exogenous to relative demand shocks. Next subsection discusses this assumption. It acknowledges situations where it is likely to be violated and adjusts the econometric specification accordingly.

Formally, our instrument is the import-weighted real exchange rate of a firm f at time t:

$$\overline{RER}_{ft} = \sum_{s} \omega_{0sf} \times \log(\mathrm{rer}_{st}), \tag{2.5}$$

with ω_{0sf} the share of goods imported from source country s, in the total imports of firm f at the initial year of the sample,[23] and with rer_{st} the real exchange rate from home (France in our

[22] See Imbs and Méjean (2015) or Chetty (2012) for instances where the price elasticity depends on the level of aggregation considered.

[23] In next section, we come back on the importance of using initial weights to compute the import-weighted exchange

application) to country s at time t. The exchange rate rer_{st} is defined using direct quotation, such that an increase of this variable implies larger costs for a firm. Moreover, the real term is computed using CPI indices. The formula of rer_{st} is:

$$\text{rer}_{st} = \text{er}_{st} \frac{\text{CPI}_{st}}{\text{CPI}_{France,t}}.$$

The pass-through from our instrument to export prices may vary across firms as a function of the extend to which a firm hedges against currency risk. To illustrate this point, consider two French firms exporting to the US: firm A imports from China while firm B simultaneously imports and exports to China. We expect that firm B will not pass through an appreciation of the Yuan as much as firm A, since she is naturally hedged against Yuan fluctuations because of her exporting activity in China. Consequently, we create a second instrument taking into account the degree of hedging of a firm. The idea is to interact importing and exporting weights for a same country by creating the following additional instrument:

$$\overline{RER}^{h}_{ft} = \sum_{s} \omega_{0sf} \times \omega^{\text{exp}}_{0sf} \times \log(\text{rer}_{st}), \tag{2.6}$$

with $\omega^{\text{exp}}_{0sf}$ the exporting weight of a firm toward destination s. We expect the pass-through from the RER on imports to export prices to be decreasing with $\overline{RER}^{h}_{ft}$. The inclusion of this second instrument will improve the strength of our first stage and therefore generate more accurately estimated exogenous price variations.

We conclude the presentation of the instruments with three remarks. First, the instrument is orthogonal to measurement errors on unit values as its construction does not involve information on exports. Therefore, our instrumental strategy deals with the measurement errors problem existing when estimating demand functions using unit values.

Second, similar instruments have been used in a series of recent international trade contributions (see Brambilla et al. (2012) or Bastos et al. (2014)). In these papers, the export-weighted exchange rate generates exogenous change in firms' destination portfolio. In our case, the import-weighted average exchange rate creates exogenous firm-specific cost shifters due to the mechanical increase of the price of imported inputs.

rate.

Lastly, we are not the first paper looking at the pass-through from the cost of imported input to export prices. Amiti et al. (2014) and Berman et al. (2012) run the same type of regression using respectively Belgian and French customs data. However, the motivation for their analysis differs greatly from ours. While, they are interested in the heterogeneity of the pass-through across firms, we only use the effect of exchange rates on export prices as a first stage to a demand function estimation. Moreover, their analysis of the pass-through from exchange rates to export prices conflates two effects: a cost shifting effect (exchange rate fluctuations impact importing costs) and a competitiveness effect. By contrast, our first stage includes a destination-year fixed effect which controls for the competitiveness effect so that the pass-through that we estimate only captures the cost shifting effect.

2.2.3 Discussion of the Identification

There are a few mechanisms that could affect the exogeneity of the instrument. First of all, the instrument is constructed from import shares, which are potentially endogenous to quality. Put simply, higher quality firms most likely import from countries with a stronger currency, from where they can source higher quality inputs (In appendix B.1, we derive a model in which the spatial structure of a firm's imports depends on the quality it produces). So we expect the instrument to be positively correlated to quality in the cross-section of firms. If not controlled for, this correlation would induce the price elasticity of demand (which is negative) to be biased upward.[24] To fix this problem, we add variety-specific fixed effects (as defined above, a variety is a firm $\times$ product category $\times$ destination combination) to our demand estimation. As a result, identification is in the time series of a variety. Since the instrument is constructed using initial import shares, its time series variations are fully driven by (firm-specific) exchange rates dynamics and not contaminated by (endogenous) import share dynamics.

Another potential problem comes from the dual impact of exchange rates variations on firm performances. While a change in exchange rates can increase input prices, it can also affect the competitiveness of firms on foreign markets. This is a concern to us as it suggests that our instrument could be correlated to a firm's demand shifter. In reality, this is not an issue with the structural

[24] In the cross-section of firms, the instrument is likely to be positively correlated to quality. So, provided that higher quality goods are more expensive, an increase in the value of the instrument is associated to an increase in both prices and the demand shifter. Hence the upward bias.

demand equation we consider. As one can see from the demand function (2.4), the competitiveness effect will be fully captured by destination-product-year fixed effect μ_{gdt}.

In order to make sure that the innocuous of this problem does not fully rely on our functional assumptions, we proceed to a robustness check whereby we exclude export flows of firms that contemporaneously import from and export to a same market (see appendix B.6, table B.3). The chances that this instrument is correlated to the demand residual through the competitiveness channel is higher for these firms. Price elasticity estimates exhibit little sensitivity to sample variations along this dimension. This is suggestive that the "competitiveness" mechanism does not drive our results.

A last threat to the identification could arise from the fact that exchange rate variations directly cause quality adjustments. Bastos et al. (2014) show that an exchange rate shock may induce a firm to upgrade its quality if it improves its competitiveness in rich destination markets. In appendix B.1, we propose a model which predicts a symmetric effect on the import side. This import side effect is based on the premise that source countries produce inputs of different qualities. When an exchange rate shock makes imports from high (low) input quality countries more affordable, a firm upgrades (downgrades) the quality of its imported inputs, and output quality adjusts accordingly.

Remark that even if firm-level quality adjustments actually arise as the real exchange rate fluctuates and firms re-balance their export and imports; it is not clear what the resulting correlation between quality and our instrument would be. An increase in $\overline{RER}_{ft}$ can equally result from the appreciation of the currency of a rich source country as of the currency of a poor source country. So the sign of the bias on price-elasticity, if any, is unclear. However, we take a conservative approach and neutralize the effect of exchange rates on quality by adding controls to the estimation. Namely, we incorporate the import weighted average GDP per capita of the firm as well as the export weighted average GDP per capita to the demand equation. The formula of these controls is:

$$\begin{cases} \overline{gdpc}_{ft}^{\text{exp}} & = \sum_s \omega_{sft}^{\text{exp}} \times \log(\text{gdpc}_{st}) \\ \overline{gdpc}_{ft}^{\text{imp}} & = \sum_s \omega_{sft}^{\text{imp}} \times \log(\text{gdpc}_{st}) \end{cases} . \tag{2.7}$$

These terms aim to capture quality adjustments following changes in the set of countries the firm imports from and exports to. The implicit assumption here is that GDP per Capita proxies the quality of inputs supplied by a country.[25] In the mechanism described above, exchange rates are suspected to affect quality only through an impact on a firm's spatial structure of imports. Controlling for that structure of exports thus makes the instrument orthogonal to the demand residual. The model presented in appendix B.1 provides a theoretical foundation to these controls.

Consistently with the above discussion, our econometric specification will proceed in two steps. In a first step, we regress the exported price of the firm on the sets of instruments, including variety and market-year fixed effects, and the controls defined in equation (2.7). Formally, the first stage is

$$\log p_{fgdt} = \eta_1 \overline{RER}_{ft} + \eta_2 \overline{RER}^h_{ft} + \beta \overline{gdpc}_{ft} + \delta_{fgd} + \delta_{gdt} + u_{fgdt} \tag{2.8}$$

with $\overline{gdpc}_{ft}$ a vector containing the two controls defined in equation (2.7), δ_{fgd} and δ_{gdt} are respectively variety and market-year fixed effects, and u is the residual term. Using the predicted values of exporting prices from this first stage, we can then estimate the structural equation (2.4) in a second stage:

$$\log r_{fgdt} = (1-\sigma)\widehat{\log p}_{fgdt} + \alpha \overline{gdpc}_{ft} + \gamma_{fgd} + \gamma_{gdt} + \varepsilon_{fgdt} \tag{2.9}$$

in which γ_{fgd} and γ_{gdt} are variety and market-year fixed effects. The estimation of this equation will be consistent if the structural error ε is orthogonal to our set of instruments. As we argue in the previous paragraphs, we believe this condition is reasonable with our specification. In equation (2.9), demand equation is identical to structural demand equation (2.4) except that we now impose our measure of quality, λ_{fgdt}, to take following form:

$$\lambda_{fgdt} = \hat{\alpha} \overline{gdpc}_{ft} + \hat{\gamma}_{fgd} + \hat{\varepsilon}_{fgdt}. \tag{2.10}$$

In the next section, we implement this methodology using French customs data. Then, we assess its effectiveness by comparing our estimates of the elasticity of demand, and the product quality to existing measures.

[25] In line with this assumption, Schott (2004) shows evidence that richer countries specialize in the export of higher quality goods.

2.3 Data and Demand Estimation Results

In this section, we apply the procedure to French exporting firms using French customs data. We start by describing the data we use, and provide descriptive statistics showing that they suit our exercise. Then, we report results on price elasticity. The estimates obtained from our empirical procedure are systematically larger, in absolute values, than corresponding OLS estimates. This is strongly suggestive that the use of our IV estimation corrects endogeneity biases described in section 2.2.2. Finally, we estimate product quality by separately estimating demand function (2.4) for different categories of goods. We document the relevancy of our quality estimates through correlations with firm-level characteristics and existing measures of quality.

2.3.1 Data

We exploit firm-level trade data collected by French customs administration. These data provide a comprehensive record of the yearly values and quantities exported and imported by French firms from 1995 to 2010. Trade flows are disaggregated at the firm, country and eight-digit product category of the combined nomenclature.[26] Imports and exports are reported separately.

Information on quantities in trade data is known to be noisy. In order to mitigate this issue, we clean the data along various dimensions. First, we drop quantities equal to one or two, since we suspect them to be subject to rounding errors or to be poorly reported by firms. Secondly, we drop prices which variations are "suspiciously" large between years, destinations, and relatively to competing products.[27] Finally, because of changes in the HS classification across years, we apply the algorithm described in Pierce and Schott (2012) in order to obtain well-defined and time invariant product categories.

Size of the Dataset As reported in the first column of table 2.1, the size of the dataset remains large after this cleaning procedure, with more than 2 million flows recorded every year. Yet, the number of observations actually used to estimate the demand system is smaller as our instrument can only be constructed for firms which have reported imports at the customs office in 1995. Third

[26]Only annual values which exceeds a legal threshold are included in the dataset. For instance, in 2002, this threshold was 100,000 euros. This cutoff is unlikely to affect our study since, this same year, the total values of flows contained in the dataset represented roughly 98 percents of the aggregated estimates of French international trade.

[27]Appendix B.3 provides the details of the cleaning procedure.

column in table 2.1 shows the size of the final sample. It appears that restricting the sample to 1995 importers induces a large loss of observations as we are left with approximately 45 percents of the total number of observations. On the positive side, the exports present in the final sample stand for two-third of total exports reported in customs data. Second column reports the size of the sample when limited to importing firms. Any firm-product-destination-year export flow for which at least one corresponding import flow can be found in the customs data for the same year and the same firm is included in this sample. Successively comparing column 1 to column 2 and column 2 to column 3 makes it possible to decompose the loss of observations. It appears that a reason why the final sample still covers a large share of total exports is that (i) exporter-importer are larger than the average exporter and (ii) exporters importing in 1995 are larger that the average exporter-importer.[28]

Table 2.1: Size of the Dataset : Importers Make most Exports

	Exports of Exporters	**Exports of Importers**	**Exports of 1995 Importers**
# **Obs.**	29,102,408	25,583,171	13,257,803
# **Varieties**	5,144,897	4,074,342	1,799,738
# **Firms**	419,624	167,692	68,255
% **Exports**	100%	98%	67.5%

Notes: An observation is an export flow at the firm, nc8 product, destination, year level. First column contains the number of observations in all the customs data. Second column reports the number of exporting flows for which importing flows are also reported for the same firm and the same year. Third column reports the number of exporting flows for which importing flows are also reported for the same firm in 1995. A variety is a firm-product combination.

The estimation of demand functions requires variations along multiple dimensions in the data. Firstly, due to the presence of market fixed effects, we need the instrument to vary across firms exporting to a given product-destination market. This implies that the set of source countries must differ between different firms supplying a same market. Secondly, because both flow-specific and market-specific fixed effects are included in the estimated equations, we respectively need (i) firms to

[28]The reader interested in applying our estimation strategy to customs data from other countries might be concerned with the fact that restricting the sample to the set of importers at the beginning of the sample period may result in a larger loss of information than in the French case. On the contrary, because exports are consistently skewed towards importing firms throughout countries, we suspect that this sample restriction will lead to a loss of information of a comparable order of magnitude in other countries. See for instance Amiti et al. (2014) for facts on the substantial skewness of exports towards importing firms in Belgium.

serve a given product-destination for many years and (ii) product-destination markets to be served by many firms simultaneously. Table 2.2 provides information about the distribution of the number of observations along these different dimensions of the data. In this table, we provide statistics for the exports of the set of firms used to identify demand equations: firms being simultaneously importers in 1995 and exporters. The median importing-exporting firm sells in four different product category, to three different destinations, and imports from four different countries. The median flow (a firm-product-destination combination) is present for three years in the sample which means that flow fixed effects are identified for more than half the observations. Symmetrically, the median market is served by two firms so the market fixed effect is identified for at least half the sample.

TABLE 2.2: Number of Observations along Multiple Dimensions

		p5	**p25**	**p50**	**p75**	**p95**	**Mean**
# **Products**	*by firm-year*	1	1	3	9	29	7.4
# **Destinations**	*by firm-year*	1	1	4	9	36	9.7
# **Sources**	*by firm-year*	1	2	4	7	15	5.3
# **Products**	*by firm-dest-year*	1	1	1	3	10	3.3
# **Destinations**	*by firm-prod-year*	1	1	1	2	9	2.5
# **Years**	*by flow*	1	1	3	7	14	4.8
# **Flows**	*by market*	1	1	2	4	15	4.2

Notes: These statistics are from firms being exporters and importers in 1995. A 'flow' is a combination of a firm, a product and a destination. A 'market' is a combination of a product, a destination and a year.

Descriptive Statistics on the Instrument The instrument crosses two informational sources: import shares and real exchange rates. Figure 2.1 reports the 1995-2010 evolution of real exchange rates for the top 5 countries regarding their total imports of French goods. After 1999, real exchange rate movements of Euro zone countries are solely due to inflation.

The instrument is constructed from 1995 import shares and intend to proxy a firm's exchange rate shocks over the period. One concern is that if import shares vary a lot over time, then the instrument is a bad proxy for real exchange rate shocks faced by firms towards the end of the period. This might generate a weak instrument issue. Table B.2 in appendix B.5 shows that autocorrelation of import shares remain large and strongly significant, such that the instrument should not lose too

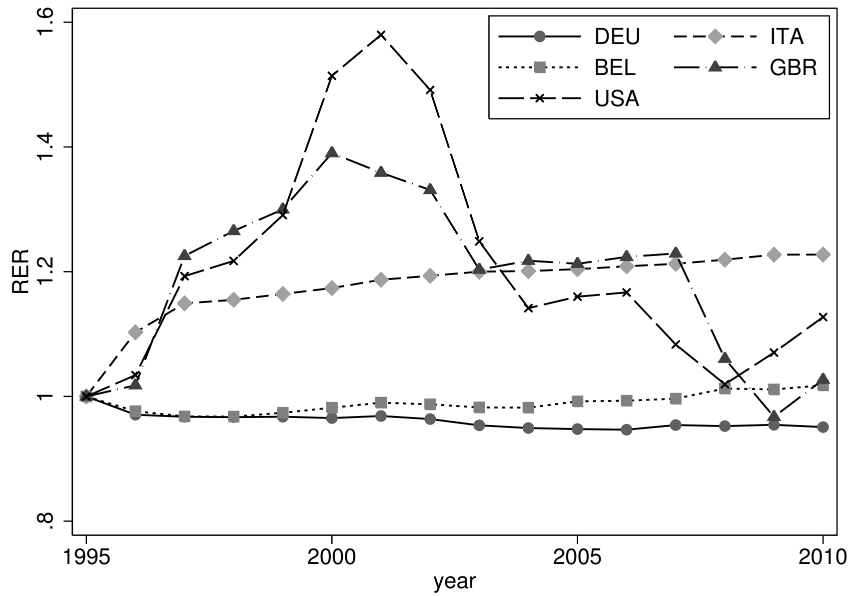

FIGURE 2.1: RER 1995-2010-Top Source Countries

Notes: Real exchange rates are calculated as $e_{Euro,st} \times \frac{\text{CPI}_{st}}{\text{CPI}_{France,t}}$ where $e_{Euro,st}$ is the direct nominal exchange rate from Euro to j's currency at date t. CPI is the consumer price index. After 1999, Real-exchange-rate movements of Euro zone countries are solely due to inflation. 1995 real exchange rates are normalized to one.

much statistical power over time.

2.3.2 Estimation Algorithm

Estimation of linear equations with two sets of high-dimensional fixed effects and unbalanced panel, as is the case in our estimation, is cumbersome. Because the panel is unbalanced along these two dimensions, the two sets of fixed effects are not orthogonal. Consequently, variables included in the regression need to be simultaneously projected on these two sets of fixed effects, as one cannot rely on successive projections. In order to do so, we rely on the algorithm developed in Guimaraes and Portugal (2010). This algorithm first demeans the variables along the two sets of fixed effects. Parameters of interest are then estimated using demeaned variables.

2.3.3 Pooled Industries Results

In order to describe the effectiveness of the instrumental strategy, we will first present results when estimating a single price-elasticity. The first stage of the estimation procedure shows that the instruments employed are strong enough, and impact export prices in a way consistent with economic theory. Then, we report the results of the second stage. Instrumentation corrects estimated coefficients as expected which provides support for the relevancy of our instrumental variable strategy.

First stage To build the instrument, we theorized that (i) exchange rate variations impact the price of imported inputs and (ii) that input prices impact output prices. As a preliminary test to our instrumental strategy, we test the first part of this causal chain. To do this, we regress the unit value of imports over the real exchange rates. A price is defined at the most disaggregate level: it corresponds to a firm, source country, CN 8 product category, year import flow. Firm-source-product fixed effects are added to the regression. Results are reported in table 2.3. As expected, real exchange rates significantly and positively impact input prices.

TABLE 2.3: Pass-through from Exchange-rates to Import Prices

	log Import Price$_{fpst}$
log RER$_{st}$	0.341***
	(0.0714)
N	22 595 549
partial R^2	0.001

Notes: Prod×Source country×Year fixed effects are included in the regression. Standard errors clustered at the source country level in parentheses. *** p<0.01

We now turn to the first stage per se. Table 2.4 shows that our instruments are strongly correlated with export prices, the endogenous variable. It presents the results of the first stage for four different specifications. Columns (1) and (2) only use the contemporaneous average exchange rate, $\overline{RER}_{ft}$, as a predictor of export prices. The difference between these two columns lies in the inclusion of the variables controlling the potential quality adjustments following changes in the GDP per capita of the average source and destination of the firm: $\overline{gdpc}_{ft}^{\text{exp}}$ and $\overline{gdpc}_{ft}^{\text{imp}}$. In columns (3) and (4) the specification is augmented with the second instrument that takes into account the degree of hedging, $\overline{RER}_{ft}^{h}$.

Three main results emerge from table 2.4. First of all, the sign of the instruments' coefficients is consistent with the theoretical predictions. An increase in the average exchange rate faced by

Table 2.4: First stage results

	log price export			
	(1)	(2)	(3)	(4)
$\overline{RER}_{ft}$	0.087***	0.092***	0.11***	0.12***
	(0.005)	(0.005)	(0.005)	(0.005)
$\overline{RER}^{h}_{ft}$			-0.31***	-0.32***
			(0.023)	(0.024)
$\overline{gdpc}^{\mathbf{exp}}_{ft}$		0.007***		0.007***
		(0.001)		(0.001)
$\overline{gdpc}^{\mathbf{imp}}_{ft}$		0.012***		0.012***
		(0.001)		(0.001)
N	9 336 602	9 124 226	9 336 602	9 124 226
Kleibergen-Paap F-stat	326.5	341.4	267.53	273.6

Notes: Dependent variable is the logarithm of the price of the exported good, at the firm×nc8×destination×year level. $\overline{RER}_{ft}$ is the import-weighted exchange rate for a firm, based on its importing shares in the first year of the sample. $\overline{RER}^{h}_{ft}$ is the import×export weighted exchange rate for a firm, based on its importing and exporting shares in the first year of the sample. $\overline{gdpc}^{\text{exp}}_{ft}$ is the average GDP per capita of the destinations of the firm. $\overline{gdpc}^{\text{imp}}_{ft}$ is the average GDP per capita of the sources countries of the firm. Partial F-statistics are computed excluding the average GDPs per capita. Firm×Prod×Dest and Prod×Dest×Year fixed effects included in all regressions. Market-level clustered standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

the firm is positively correlated with the price of its exported output. As an average effect, we find an elasticity of 0.1 between imported exchange rates and output prices. Moreover, we see that our second instrument is also consistent with the theory. Firms whose exporting shares are correlated with importing shares are less affected by exchange rate changes. Secondly, the coefficients on the GDP per capita are also consistent with theory. As predicted in Bastos et al. (2014), following an increase in the average GDP per capita of its destinations, a firm should upgrade its product, generating a positive impact on prices. Similarly, the average gdp per capita of source countries is positively correlated with output prices, suggesting that $\overline{gdpc}^{\text{imp}}_{ft}$ actually proxy for the quality of imported inputs. One can notice that the introduction of these two terms does not affect the relationship between the instrument and output prices. This suggests that the bias from not controlling for the quality response to exchange rate fluctuations is small. As mentioned earlier, there is no reason to think that the cost shifter generated by exchange rates variations should induce systematic changes in the quality choices made by firms. Therefore, it is not surprising to see that these two controls do not affect the strength of our instruments. Finally, we also observe that our set of instruments display a strong correlation with exported prices. With partial F-statistics ranging from 267 to 341, weak instruments are not an issue here.

Second stage After checking the validity of the first step, we use prices predicted by our set of instruments as an exogenous variable in the demand equation. We estimate the demand equation using the four different specifications displayed in table 2.4. Moreover, in order to assess the effectiveness of our instrumental strategy, we compare our result to a specification using OLS, that does not address the endogeneity problem. Results are displayed in table 2.5. We number columns so that second stage specifications have the same number as corresponding first stage specification in table 2.4. In addition, column (0) presents the results of the OLS specification.

TABLE 2.5: Second stage results

	Log Export Sales				
	(0) OLS	(1) IV	(2) IV	(3) IV	(4) IV
Log price $(1-\hat{\sigma})$	**0.17***** (0.002)	**-1.38***** (0.20)	**-1.35***** (0.18)	**-0.86***** (0.14)	**-0.82***** (0.13)
$\overline{gpdc}_{ft}^{\mathbf{exp}}$			0.15*** (0.003)		0.15*** (0.003)
$\overline{gpdc}_{ft}^{\mathbf{imp}}$			0.027*** (0.003)		0.021*** (0.002)
Instrument	.	Single	Single	Hedg.	Hedg.
N	9 336 602	9 336 602	9 124 226	9 336 602	9 124 226

Notes: The dependent variable is the logarithm of export sales, at the firm×nc8×destination×year level. Log price is the prediction from the first stage. $\overline{gdpc}_{ft}^{\text{exp}}$ is the average GDP per capita of the destinations of the firm. $\overline{gdpc}_{ft}^{\text{imp}}$ is the average GDP per capita of the sources countries of the firm. Firm×Prod×Dest and Prod×Dest×Year fixed effects included in all regressions. Market-level clustered standard errors in parentheses, adjusted for the two stages estimation procedure. *** p<0.01

Table 2.5 contains several indicators of the good performance of our instrumental strategy. The coefficient for the OLS regression in column (0) is biased due to simultaneity and measurement errors problems. Whereas measurement errors drive the estimate toward zero, the simultaneity problem generates a positive bias on the estimation of the elasticity. These predictions are confirmed with a positive coefficient of 0.17 for the OLS specification. By contrast, when using our sets of instrumental variables, the estimates for the price coefficient is lower, ranging from -0.82 to -1.38. This implies estimates of the price-elasticity of demand ($-\hat{\sigma}$) ranging from -1.82 to -2.38, which are consistent with recent findings in the literature.[29] Moreover, coefficients on variables $\overline{gdpc}_{ft}^{\exp}$ and $\overline{gdpc}_{ft}^{\mathrm{imp}}$ are also consistent with the theory, since they reveal that products sourced and supplied to richer countries are of better quality (i.e. they are more sold, conditional on price). Finally, it is noteworthy that the estimates are consistent across specifications, even tough the specifications with two instruments seem to generate a slightly smaller magnitude of the coefficients.[30]

Estimating a single coefficient for all industries shows that instrumenting affects price elasticity estimates in a direction consistent with a correction of the simultaneity bias. However, in order to infer quality measures from these demand equations, we separately apply this method to different product categories.

2.3.4 Demand Estimation by Industry

In this section, we describe the results obtained by replicating the instrumentation strategy separately for fifteen product categories.[31] We use the set of instruments displayed in column (4) of table 2.4. As a way to make our first stage as strong as possible, this specification includes the instrument taking into account the degree of hedging, as well as the GDP per capita control variables.

Product-specific price-elasticity estimates The results of this procedure are displayed in table 2.6. For each product category, we report the IV and OLS estimates of the price-elasticities of demand, as well as the F-statistics of the first stage of the instrumental variable procedure.

As reported in table 2.6 the IV estimated coefficient is more negative than its OLS analogue in most industries. This is consistent with our instrument correcting the simultaneity bias that links quality and prices in demand equation. While some OLS estimates are positive (which is possible

[29] Recent papers estimating firm-level demand functions include Nevo (2000), who finds estimates between -2.2 and -4.2 in the cereal industry, Dubé (2004) who gets estimates between -2.11 and -3.61 in the soft drinks industry. Some recent studies estimate firm-level price-elasticities for several industries. Foster et al. (2008) obtains a mean estimate of -2.41 with eleven homogeneous industries, Handbury (2012) finds a mean of -1.97 with 149 industries, and Gervais (2015) a median of -2.11 with 504 products.

[30] Appendix B.6 provides robustness checks about the procedure, excluding sensible years, as well as using first and longer differences. These variations do not affect the effectiveness of the instrumentation.

[31] Unfortunately, when estimating at a more disaggregated level of the product classification, the number of observations per product category decreases and our instruments becomes weak in an important subset of product categories.

TABLE 2.6: Price-elasticity estimates ($-\sigma$) for different product categories

Product categories	OLS		IV		
	Coef ($-\hat{\sigma}$)	SE	Coef ($-\hat{\sigma}$)	SE	F-stat
Animal Products	-0.83	(0.015)	**13.3**	(20.3)	1.17
Textiles	-0.69	(0.004)	**-0.80*** **	(0.14)	331.9
Metals	-0.81	(0.006)	**-0.87***	(0.46)	22.3
Vegetable Products	-0.81	(0.011)	**-0.93**	(2.27)	1.91
Foodstuffs	-0.95	(0.007)	**-0.97**	(0.81)	11.8
Machinery, Electrical	-0.85	(0.004)	**-1.23*** **	(0.29)	40.8
Wood, Wood products	-0.79	(0.007)	**-1.27**	(1.08)	2.93
Chemicals and Allied	-0.90	(0.006)	**-1.51*** **	(0.63)	12.9
Plastics, Rubbers	-0.86	(0.008)	**-2.27*** **	(0.68)	12.6
Miscellaneous	-0.76	(0.005)	**-2.72*** **	(0.57)	9.75
Transportation	-0.71	(0.012)	**-3.20*** **	(0.56)	23.85
Stone, Glass	-0.82	(0.009)	**-4.55*** **	(1.03)	4.93
Mineral Products	-0.81	(0.022)	**-4.75*** **	(1.80)	2.30
Footwear, Headgear	-0.72	(0.013)	**-4.84*** **	(1.36)	3.6
Raw Hides, Skins, Leather	-0.77	(0.010)	**-5.98*** **	(0.86)	8.08

Notes: Each row corresponds to a product category for which the demand equation is estimated. The IV specifications use the average exchange rates as instruments $\overline{RER}_{ft}$, in addition to the hedging term, $\overline{RER}^{h}_{ft}$, and the two gdp per capita controls,$\overline{gpdc}^{exp}_{ft}$ and $\overline{gpdc}^{imp}_{ft}$. Last column provides the value of the partial F-statistic of the first stage of the 2SLS procedure. Firm×Prod×Dest and Prod×Dest×Year fixed effects are included in all regressions. Standard errors are clustered at the market level. * p<0.1, ** p<0.05, *** p<0.01

if both sales and prices go up as quality increases) our IV estimates are almost all negative, and in a range consistent with the existing literature in Industrial Organization. As an outlier, the first product category, related to Animal Products, records a very large, positive and imprecise price elasticity estimate.[32] Because of this, we will not use this category to construct quality estimates for the rest of the paper. Excluding this industry, our estimates range from -0.80 to -5.98.

As a way to assess the reasonableness of our price elasticity estimates, we correlate them to Sutton (2001)'s measure of vertical differentiation. Our expectation is that in vertically differentiated sectors, consumers are more sensitive to quality and less to prices. The reason being that there is a positive correlation between the degree of vertical correlation and the degree of horizontal differentiation across industries. As shown by figure 2.2, the demand faced by exporters of vertically

[32]It is intuitive to understand why this empirical strategy fails in the case of "Animal products", since this industry is likely to have a very small share of imported goods among its input. Similarly, we can notice that the category "Vegetable products" also displays low first stage F-stat, presumably for identical reasons.

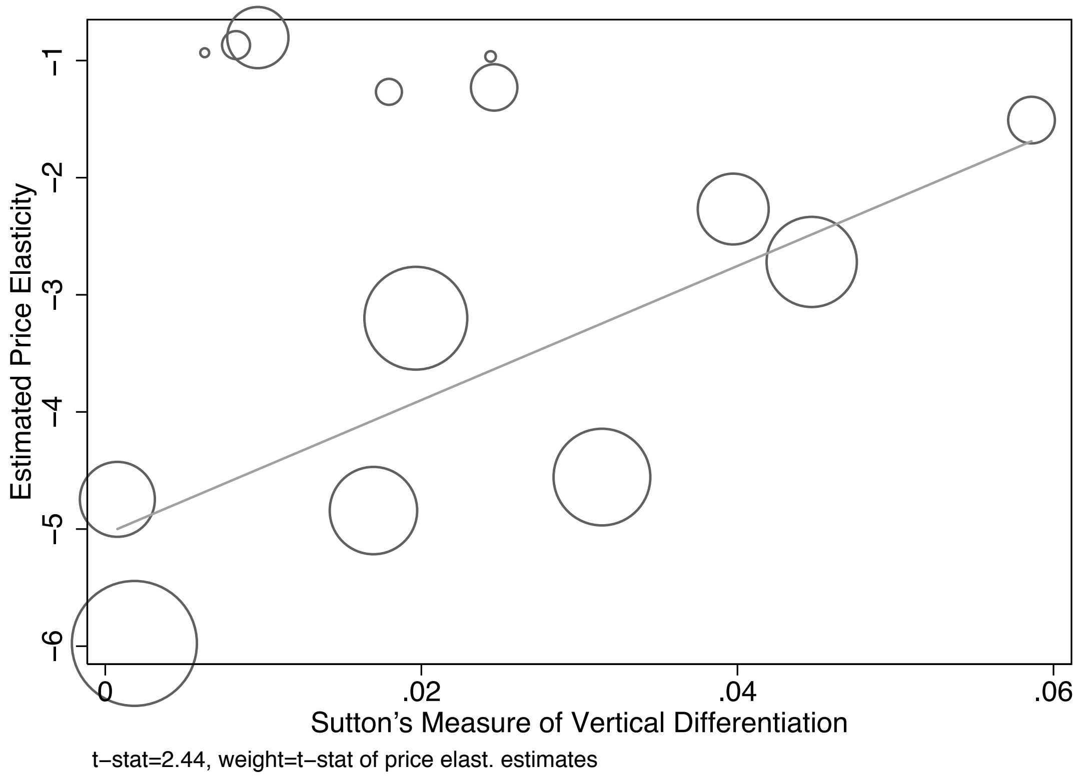

FIGURE 2.2: Price Elasticity Versus Vertical Differentiation

Notes: Each circle corresponds to a product category, i.e. a 1-digit position of the HS classification. The size of a circle is proportional to the absolute value of the t-statistics on $1-\sigma$. The x-axis is Sutton (2001)'s measure of vertical differentiation, i.e. the share of R&D and advertising expenditures in a sector's total sales. The y-axis is equal to estimated price-elasticity. The line is the predicted value of a weighted OLS regression of price-elasticity over Sutton's measure. Weights are the absolute value of the t-statistics on $1-\sigma$. "Animal Products" excluded from the regression.

differentiated products is significantly more elastic, which is consistent with our prediction.

2.4 Analysis of Estimated Quality

Once demand functions have been estimated, we can obtain measures of quality by applying equation (2.10). As a first way to describe our quality estimates of quality, we provide a variance decomposition in table 2.7. Here, it is important to remember that the quality measure is obtained at the firm $\times$ product category $\times$ destination $\times$ year level. Moreover, quality is defined relatively to the average quality in the market. Therefore, it defines a position over the quality ladder in a market, rather than an absolute quality which can be compared across markets. One can see from table 2.7 that the dispersion of quality is well predicted by variety-specific effects. Indeed, half of this quality dispersion is captured by time-invariant variety-specific effects, and two thirds by time-variant variety fixed effect. From this table, it seems that the quality level of a product is strongly correlated across destinations for a specific good. We will rely on this evidence that quality choices are made at the variety level, when identifying quality upgrading in a destination from competition shocks in other destinations served by a variety.

Table 2.7: Variance Decomposition of the quality measure

	Quality λ_{fpdt}			
Firm FE	✓			
Firm×Product category FE		✓		
Firm×Year FE			✓	
Firm×Product category×Year FE				✓
R^2	0.17	0.51	0.23	0.69

Notes: Each column corresponds to the regression of our quality measure from table 2.6 on a different set of fixed effects. Measures from "Animal products" are excluded. Product category are defined at the 8-digit level.

Interestingly, there is substantial quality variation within varieties across destinations. Controlling for Firm×Product category×Year FE, we can predict 69 percents of the variation of our quality measure. This is suggestive of the presence of market-specific tastes, or of the fact that firms adjust the quality to their product depending on the country they serve.

2.4.1 Consistency tests

In order to assess the relevancy of our measure, we compare it to several existing measures.

Comparison with expert assessed quality First, we relate it to one of the only objective product quality measure existing in the literature. Crozet et al. (2012) take advantage of expert ratings for Champagne to analyze the importance of quality in explaining international trade flows at the firm level. These expert assessed ratings (initially from Juhlin (2008)) are expressed in number of stars ranging from 1 to 5, one being the lowest quality. We non-parametrically regress our revealed measure of quality for Champagne exports over the number of stars.[33]

Table 2.8: Correlation with Ratings of Champagne Exports

	Estimated quality λ_{fpdt}
2 Stars	0.060***
	(0.006)
3 Stars	0.112***
	(0.006)
4 Stars	1.245***
	(0.005)
5 Stars	1.421***
	(0.007)

Notes: Champagne ratings from Juhlin (2008). A larger number of star means a higher expert assessed quality. We drop non-Champagne exports of Champagne producers. Robust standard errors in parentheses. *** $p < 0.01$

From table 2.8 it appears that our measure of quality is monotonically increasing with the number of stars assigned by Juhlin (2008). Even though Champagne is a specific good in many dimensions, and cannot assess the overall quality of our measure, this is convincing of the relevancy of our measure of quality.

Correlation with firms' characteristics In order to further improve our understanding of the characteristics of our quality measure, we relate its estimated value to firms' characteristics. We merge our estimated qualities with firm-level data from France.[34] Therefore, we are able to inspect how our quality measure is able to explain firm characteristics such as the average wage. Table B.4 displayed in appendix B.7.1 inspects these correlations using the number of employees of the firm, its average wage, and our estimates of quality. It documents a strong and positive correlation between our quality measures and the average wage paid by the firm. Moreover, this significant

[33]We thank the authors for sharing their data

[34]We use the dataset BRN, that covers all French firms with revenue larger than 763 Keuros, and is constructed from reports of French firms to the tax administration.This dataset has been widely used in the literature (see Eaton et al. 2011 or Berman et al. 2012 for instance).

correlation is robust to the inclusion of the number of employees as regressor explaining the wage of the firm. These results provide more evidence that our measure captures heterogeneity across firms that is related to product quality differences.

Length of quality ladders and vertical differentiation As a final test of our quality estimation, we construct a market specific measure of the "length" of the quality ladder. Following Khandelwal (2010), for any product, destination, year combination, this length is obtained by taking the difference between the 95th and the 5th percentile of the quality distribution. This measure may be interpreted as a revealed measure of the degree of vertical differentiation of a market. As such, it should be positively correlated to Sutton (2001)'s alternative measure of vertical differentiation. Table B.5, displayed in the appendix B.7.2, confirms this conjecture as it shows that both measures are positively and significantly correlated.

2.4.2 How well do Prices proxy for Quality?

As a last way to analyze the properties of our measure of quality, we look at the relationship between estimated quality and export prices. This is an important point since prices have been extensively used in the literature as a proxy for quality. The problem is that prices are supposedly also a function of a firm's production cost. Therefore in sector with little vertical differentiation, prices should poorly capture differences in demand fundamentals, whether across firms or over time. To test this intuition, we regress (log) prices over estimated quality and we allow the slope of the relationship to depend on Sutton's measure of vertical differentiation.

Results for this exercise are reported in table 2.9. A first finding is that there is a positive relationship between estimated quality and prices in all sectors. However, the slope of that relationship is significantly steeper in more vertically differentiated industries, consistently with the intuition presented above. This is true whether we look in the cross-section of a market (column (1)) or in the dynamics of a flow (column (2)). To get a sense of the magnitude of the differences in slope across sectors, let us compare the quality-elasticity of prices between "mineral products" and "chemical and allied", respectively the least and the most vertically differentiated product categories. In "mineral products", the quality-elasticity of prices is approximately 0.035 when it is about 0.11 in "chemical and allied". This means that prices are three time less informative on quality for "mineral

Table 2.9: Prices and Quality across Sectors

	log *Export Price*$_{fpdt}$ (1)	(2)
Quality λ_{fpdt}	0.033***	0.025***
	(0.000)	(0.001)
Quality$_{fpdt}$ $\times$ **Sutton**$_p$	1.260***	1.048***
	(0.005)	(0.018)
Market Effects	YES	YES
Flow Effects	NO	YES
N	13 542 905	13 542 905
R-squared	0.845	0.983

Notes: Dependent variable is the logarithm of exports unit value at the firm×nc8×destination×year level. 'Sutton' is the share of advertising and R&D expenditures in a US sector's sales. It is computed at the 4 digit level of ISIC-rev 4 classification by Kugler and Verhoogen (2012). A flow is a firm×nc8×destination combination. A market is a nc8×destination×year combination. Market-level clustered standard errors in parentheses. *** $p < 0.01$

products" than for "chemical and allied".

2.5 Quality Response to Low-Cost Competition

In this section, we exploit our measure of quality to document the quality response of French firms to low-cost competition. We start by describing this identification strategy. We then report the results of the estimation.

2.5.1 Identification strategy

Following Bernard et al. (2006), we define low-wage countries' competition (LWC) as the share of imports from countries with a GDP per capita inferior to 5% of French GDP per capita. More specifically, LWC is constructed from bilateral trade dataset BACI, according to the following formula:

$$LWC_{pdt} = \frac{I^{\text{low}}_{idt}}{I_{idt}}, \tag{2.11}$$

where I^{low}_{idt} is country d's imports of 6-digit HS product i from low-wage countries at date t. Respectively, I_{idt} is country d's total imports of product i at date t. In equation (2.11), p is an 8-digit

CN product position which belongs to 6-digit HS category i.[35]

A natural way to identify the within-firm quality response to LWC would be to regress the dynamics of the quality measure, λ_{fpdt}, over the dynamics of LWC_{pdt}. Since LWC does not vary across firms within a market, this approach would amount to looking at the impact of LWC over the mean quality of exports in a market. The problem is that our measure of quality is defined relatively to the average quality in a market. So its market-level mean is normalized to zero and is constant over time. As a consequence, identification requires variation in low-cost competition across firms, within a market.

In order to generate such variation, we make use of the information on multi-destinations exporters. Within a market, firms differ in the other markets they serve simultaneously. Therefore, for any given market, we can construct a measure of the competition faced by a firm-product variety in the rest of the world. Let LWC^{ROW}_{fpdt} be that measure and let t_{0fp} be the first year when variety fp is observed in the sample. LWC^{ROW}_{fpdt} verifies:

$$LWC^{ROW}_{fpdt} = \frac{\sum_{d' \neq d} r_{0fpd'} \times LWC_{pd't}}{\sum_{d' \neq d} r_{0fpd'}},$$

with r_{0fpd} the sales of variety fp in destination d, at initial date t_{0fp}.

In the cross-section of a market, a variety with a higher LWC^{ROW} faces a fiercer low-wage competition in the rest of the world. Our identification strategy consists in correlating the dynamics of LWC^{ROW}_{fpdt} with the dynamics of λ_{fpdt}. Since the competition shocks that we exploit occur in a market different from the quality adjustments we intend to identify, our identifying assumption is that quality variations are correlated across destinations within a variety. In the extreme case where a variety is served with a same quality in all destinations, our strategy would capture the exact impact of a local competition shock on local quality. In general, the effect we estimate will be discounted for the fact that qualities do not perfectly co-move across destinations. Therefore, our econometric specification is:

$$\lambda_{fpdt} = \sum_{\tau=0}^{5} \beta_\tau LWC^{ROW}_{fpd,t-\tau} + FE_{fpd} + FE_{pdt} + u_{fpdt} \tag{2.12}$$

[35] Documentation about BACI can be found in Gaulier and Zignago (2010)

with FE_{fpd} a set of flow fixed effects and FE_{pdt} a set of market fixed effects. Model (2.12) identifies the effect of competition on quality, up to a five years lag. FE_{pdt} controls for the fact that competition in the rest of the world could be correlated to local competition shocks. Flow fixed effect FE_{fpd} controls for the average quality of a flow over the period. Flow fixed effects are included because in the cross-section of a market, quality might be correlated to LWC^{ROW}_{fidt} through the self-selection of firms into export markets over quality. For instance, high quality firms might self-select into markets with stronger low-wage competition. The inclusion of flow-fixed places the estimation in the dynamics of a trade flow. As we use initial export shares to construct LWC^{ROW}, its dynamics is not driven by some (endogenous) reallocation of exports.[36]

Given our fixed effect specification, our identifying assumption is that the relative dynamics of LWC^{ROW} across firm-product-destination trade flows, within a product-destination market are exogenous to relative dynamics in quality shock u_{fpdt}. Next subsection presents our results.

2.5.2 Results

In this subsection, we show the results obtained by estimating variants of equation (2.12). In particular, specifications differ in the number of lags we estimate. Results from our main specification are reported in table 2.10: we run specification (2.12) first by including each lag of rest-of-the-world competition separately and then by including all lags together. In order to make regressions comparable, we use a same sample of firms for which we observe at least five lags of rest-of-the-world competition.[37] Overall, table 2.10 suggests quality upgrading triggered by low-cost competition, but only after a few years. In facts, low-cost competition appears to only have an effect on quality upgrading after three years. A coefficient 0.196 associated to LWC^{ROW}_{t-4} means that a 10 percentage point increase in the competition faced by a firm in the rest of the world causes four years later a 2% point increase in the quality supplied by the firm to the market under consideration. The fact that the effect of competition takes time to occur is a reasonable result. Indeed, our measure of quality is revealed from the demand faced by a firm. No matter the way the firm upgrades the quality of its products, it seems sensible to think that it does not instantaneously result into larger sales as

[36]In Appendix B.8, figure B.1 describes the penetration of low-wage countries by year in the top five largest destination countries for French exporters.

[37]A potential concern is the endogenous attrition of exporters due to low-cost competition. Keeping a constant set of exporters avoid this mechanism to drive the results.

consumers need time to become aware of the upgrade and to adjust their demand accordingly.

Table 2.10: Low-wage Competition and Quality Upgrading.

	Dep. variable: Quality $\lambda_{f,p,d,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LWC_t^{ROW}	0.003						0.008
	(0.060)						(0.060)
LWC_{t-1}^{ROW}		-0.038					-0.051
		(0.061)					(0.061)
LWC_{t-2}^{ROW}			0.066				0.053
			(0.062)				(0.062)
LWC_{t-3}^{ROW}				0.122**			0.086
				(0.066)			(0.065)
LWC_{t-4}^{ROW}					0.196***		0.165**
					(0.066)		(0.066)
LWC_{t-5}^{ROW}						0.137**	0.106
						(0.067)	(0.067)
Observations	850 051	850 051	850 051	850 051	850 051	850 051	850 051
R^2	0.94	0.94	0.94	0.94	0.94	0.94	0.94

Notes: Quality measures are obtained from table 2.6, excluding "Animal products". Flow and Market fixed effects included in all regressions. Market-level clustered standard errors in parentheses. * p<0.1, ** p<0.05,*** p<0.01.

In order to gain confidence into the fact that the effect we capture in table 2.10 is indeed a quality upgrading response to competition, we now interact our measure of competition with a sectoral measure of the vertical differentiation. Our prediction is that the effect of competition should be larger for more vertically differentiated sectors as firms from homogeneous sectors can not adjust their quality. This prediction is confirmed in table 2.11. More specifically, we see that the interaction term is significant for the third and fourth lag, in addition to the contemporaneous level of competition. This confirms the fact that the effect we identified in 2.10 is driven by firms from vertically differentiated sectors.

Overall, these results are very suggestive that firms upgrade their quality when the penetration of low-wage countries go up. However, this response appears to take a few years to be effectively transmitted to sales, and therefore profits.

TABLE 2.11: Is Quality Upgrading more Significant in more Vertically Differentiated Sectors?

	Dep. variable: Quality $\lambda_{f,p,d,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LWC_t^{ROW}	-0.115						-0.112
	(0.096)						(0.097)
$LWC_t^{ROW} \times$ Sutton	6.462**						6.638**
	(2.628)						(2.653)
LWC_{t-1}^{ROW}		-0.043					-0.004
		(0.098)					(0.098)
$LWC_{t-1}^{ROW} \times$ Sutton		-0,899					-2.939
		(2.678)					(2.723)
LWC_{t-2}^{ROW}			-0.090				-0.069
			(0.101)				(0.102)
$LWC_{t-2}^{ROW} \times$ Sutton			-2.437				0.961
			(2.820)				(2.911)
LWC_{t-3}^{ROW}				-0.050			-0.019
				(0.101)			(0.102)
$LWC_{t-3}^{ROW} \times$ Sutton				6.358**			4.134
				(2.667)			(2.779)
LWC_{t-4}^{ROW}					-0.034		-0.051
					(0.104)		(0.105)
$LWC_{t-4}^{ROW} \times$ Sutton					9.561***		9.251***
					(2.755)		(2.882)
LWC_{t-5}^{ROW}						0.123	0.163
						(0.103)	(0.104)
$LWC_{t-5}^{ROW} \times$ Sutton						0.971	-2.179
						(2.756)	(2.835)
Observations	679,342	679,342	679,342	679,342	679,342	679,342	679,342
R^2	0.94	0.94	0.94	0.94	0.94	0.94	0.94

Notes: Quality measures are obtained from table 2.6, excluding "Animal products". Flow and Market fixed effects included in all regressions. Market-level clustered standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

2.6 Conclusion

A recent literature has evidenced that product quality has implications for key economic outcomes such as firms' profitability or welfare inequalities. These findings make it crucial to understand the determinants of quality at the firm-level. In this paper, we have provided a necessary tool to pursue this research agenda. Namely, we have proposed a novel strategy to estimate time-varying quality at the firm-level. Our strategy is robust to unobserved vertical differentiation. It only requires firm-product level information on prices, sales and imports by country.

We identify quality by estimating a demand function at the firm-product level. Quality is obtained as a residual of demand, once prices have been controlled for. In order to deal with the endogeneity of prices in the demand function, we construct a new firm-specific instrument. This instrument interacts variations in exchange rates with firm-specific importing shares. We implement our estimation on French customs data and get a number of elements supporting the reliability of our approach.

As a first application to our method, we compare (export) prices, a widely used proxy for quality, with our export quality estimates. We find a positive and significant relationship between quality and prices, however, this relationship is weaker in more homogeneous sectors. These results hold in the cross-section as well as in the dynamics of a firm. Our findings calls for a cautious use of prices to measure quality.

Finally, we use estimated quality, along with information on low-wage countries penetration rates to identify the quality response of firms' exports to low-wage countries' competition. Our results suggest that firms upgrade their quality when competition intensifies. This result is important for policy analysis as it reveals a new channel through which exporting firms can mitigate the effect of low-wage competition.

Chapter 3

Advertising expenditures across heterogeneous firms

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[1] I would like to thank Eric Verhoogen and Jonathan Vogel for comments and guidance.

3.1 Introduction

In 2007, expenditures in advertising accounted for 2% of the GDP in the United States. Yet, advertising has only recently been integrated in macroeconomics and international trade models. Recent and important examples are Arkolakis (2010, 2016) and Drozd and Nosal (2012). In these models, advertising is introduced in order to create friction when firms wish to extend their market shares, and, therefore, can explain heterogeneous or slow responses of firms following a change in the market conditions.

In this paper, I conduct an empirical study about the use of advertising at the plant level, taking advantage of information about advertising expenditures in the manufacturing census from Chile. In particular, I show that, within a defined industry, the advertising intensity of a firm - measured by the advertising expenditures as a share of sales - is positively correlated with its size. Moreover, this pattern appears to be even stronger in industries with a large scope for vertical differentiation. This pattern is consistent with an extension of a model of advertising with heterogeneous firms from Arkolakis (2010) in which firms can use advertising to affect the perceived quality of their product.

In the next section, I present the justification of this paper by describing the positive correlation between advertising intensity, measured by the advertising expenditures as percentages of the total sales, and the size of the firm, measured by the log of the number of employees. This correlation appears between firms producing simultaneously within the same industry, such that this correlation cannot be explained by industry or time characteristics. Moreover, I show that this correlation is stronger in vertically differentiated industries. Indeed, when regressing separately highly vertically differentiated industries, the slope between advertising intensity and size appears to be steeper than when looking at industries with a small scope for vertical differentiation.

In section 3.3, I develop a model of advertising at the firm-level, following Arkolakis (2010). In addition to selecting their number of potential consumers, firms can also affect the aggregate perceived quality of their products by using a costly marketing technology. This model is derived in a framework where firms are heterogeneous. However, this heterogeneity is defined in terms of quality rather than productivity.[2] This additional feature of advertising, which is not featured in Arkolakis (2010), allows me to predict an increasing advertising intensity when the size of the firm

[2] I therefore follow a quality-version of the heterogeneous firms model presented by Melitz (2003), as described in Baldwin and Harrigan (2011)

increases. The intuition is the following: when only considering an extensive margin of consumers, the marginal benefit of advertising is constant (equal to a new customer) while the advertising costs are increasing (because each new customer is more costly to reach than the previous one). However, affecting perceived quality generates increasing returns of advertising with the size of the firm. This explains why larger firms will spend relatively more in advertising when they are able to affect the quality of their product, as perceived by the consumer. Moreover, the slope of this relationship between size and advertising intensity will be increasing with the ability of the firm to vertically differentiate its product.

Finally, in section 3.4, I return to the data. I test the theory by showing that the positive correlation between size and advertising intensity presented in section 3.2 cannot be explained by alternative mechanisms that could predict this same correlation. Moreover, using two measures of vertical differentiation from Sutton (2001) and Khandelwal (2010), I confirm that this positive correlation is stronger in industries where the scope for vertical differentiation is large. This brings support to the idea that the positive correlation observed in the data is explained by this ability for a firm to affect the valuation of their product through advertising.

This paper draws from the extensive literature about advertising in Industrial Organization. For many years, researchers have identified two features of advertising. Chamberlin (1933) already distinguished an advertising that aims to inform consumers, from one that affects consumers' valuation of the good. The former has been subsequently named "informative" advertising, while the latter is characterized as "persuasive". Butters (1977) was the first to develop a formal model of informative advertising, featuring increasing marginal costs of advertising, while Stigler and Becker (1977) is often described as the first model of persuasive advertising. More recently, Rauch (2013) inserts these two features in a single model of advertising, in order to show how these two types have opposite predictions of welfare. In addition to this theoretical literature, empirical studies have investigated the importance of economies of scale in advertising. For instance, Brown (1978) finds evidence of such economies in the cigarette industry, while Seldon, Jewell, and O'Brien (2000) suggest the presence of diseconomies of scale in advertising for the beer industry. Overall, Bagwell (2005) summarizes that advertising seems to display increasing returns up to a threshold, after which returns appear to decrease.

This paper is also closely related to recent literature in international trade. Numerous papers have recently focused on the role played by product quality as a result or a determinant of the exporting activity (see Verhoogen (2008) or Hallak and Sivadasan (2013) for example). In these papers, a product needs to satisfy quality requirements to fit the needs of foreign consumers, and therefore be able to reach foreign markets. This can be done by upgrading the quality of your product, or simply by creating a good reputation for the good you produce. With this view, persuasive advertising could spur the export of high-quality products, but also be a determinant of the exporting activity by itself. Kugler and Verhoogen (2012) develops such a framework where quality and a fixed investment (that can be interpreted as advertising) are complementary in generating the reputation of a product. In my paper, the model does not emphasize this link with the exporting activity; it precisely describes how advertising expenditures are determined by the quality of the product. Therefore, it draws a similar complementarity between the use of advertising of a firm and the product quality.

Finally, this model of persuasive advertising has a second advantage in terms of empirical predictions over a standard model of informative advertising. By allowing the firm to affect the perceived quality of its product, it gives the advertising activity the ability to affect the market power of producers. Numerous papers have documented the existence of prices heterogeneity across destinations (see Bastos and Silva (2010) or Manova and Zhang (2012) for instance). This type of heterogeneity cannot be explained by the firm productivity alone since it features differences for a similar good produced by a single firm. However, the existence of a destination-specific reputation for this good could explain this price heterogeneity. The persuasive advertising model developed in this paper can be seen as a first step toward a model explaining prices and quantity heterogeneity across destinations.

The next section illustrates the motivation of this paper, by displaying the main empirical finding, namely the positive correlation between advertising intensity and size.

3.2 Empirical motivations

To my knowledge, no empirical study has specifically looked at the link between advertising intensity and size at the firm-level. This is likely due to the scarcity of large firm level datasets providing information about advertising expenditures. In this section, I aim to rectify this gap by taking advantage of the census of manufacturing firms from Chile. This plant-level dataset provides information about the amount spent in advertising by all Chilean manufacturing firms that are larger than 10 employees. I will therefore be able to estimate the relationship between the advertising intensity (measured by advertising expenditures as a share of total sales) and the size of a plant.

I start this section by describing the dataset, and then I will turn to the empirical analysis.

3.2.1 Dataset

The Encuesta Nacional Industrial Anual (ENIA) provides firm and product-level data from Chilean plants extracted from the industrial survey conducted by the Statistical National Institute of Chile. The sample covers approximatively 5000 plants after cleaning,[3] from 1995 to 2007. This dataset contains common information at the firm level such as sales, productive factors and exporting activity. However, as a notable feature, this dataset provides information about the amount spent by the firm in "advertising and promotional activities". It is important to note that we only observe a single number at the plant level. Consequently, it is impossible to allocate this amount across the products of the plant or the markets it is serving. Therefore, I will neither be able to pursue this analysis at the product level, neither to relate these expenditures to product or market-level variables.

In order to provide a first look at the data, I provide, in the table 3.1 summary statistics for the year 1996, describing the distribution of advertising intensities among different subcategories of plants. While the average advertising intensity is 0.54% this year, we can notice that more than half of the plants (54 %) report no spending in advertising. More interestingly, the average advertising intensity, conditional on using advertising, reaches 1.17%. These numbers may seem small at first glance. However, the dataset only consists of manufacturing plants. This could explain why these numbers are lower than statistics usually mentioned to describe the importance of advertising.[4]

The existence of this heterogeneity is likely to be explained by the industry and firm heterogeneity. As an example, I provide in this table the average spending in advertising, as percentages of sales, separately for exporters and non exporters, and according to the degree of differentiation

[3]In order to avoid the role of outliers in predicting empirical patterns, the cleaning procedure consists of excluding plants whose employment levels and advertising intensities are doubtful. Therefore, I drop establishments whose employment is lower than 10 as well as those whose advertising intensity is above the 99th percentile of the industry-year distribution.

[4]In the US for instance, advertising expenditures account for 2% of the GDP

of the industry.[5] We can therefore see that exporters and plants in differentiated industries appear to have higher shares of sales spent in advertising.

Table 3.1: Summary statistics for Advertising Intensity (year 1996)

Sample		**Mean**	**Mean SD.**	**Max**	**N**
Total	All	0.54	0.029	70.68	5417
	Only advertising firms	1.17	0.060	70.68	2488
Exporters	No	0.41	0.029	70.68	4269
	Yes	1.01	0.078	27.16	1148
Diff. industries	No	0.37	0.019	13.86	2753
	Yes	0.96	0.088	70.68	1627
Mult. Products	No	0.32	0.026	21.79	2023
	Yes	0.66	0.043	70.68	3394

Notes: Summary statistics for advertising intensity defined by the amount spent in advertising as percentages of total sales. Numbers are only from the year 1996.

Therefore, it appears necessary, when trying to explain the heterogeneity existing between firms, to consider industry, but also firms characteristics. Before looking at heterogeneity between plants in a similar industry, it is useful to first look at heterogeneity in terms of advertising between industries. This will help to have a sense of which industries are spending large amounts in advertising. The following table 3.2 aims to do so by providing the ranking of industries according to the average advertising intensity of their firms.

We observe a large heterogeneity across industries. This is not surprising since the products described above are different in many dimensions. This table also enables us to distinguish which kind of industries will intensively use advertising. It thus appears that products at the top of the ranking are mainly final goods, directly purchased by the consumer. Inversely, industries recording low advertising intensities are intermediate producers, whose products are destined for other firms.

However, the goal of this paper is to look at the heterogeneity existing between plants within a same industry. Literature in Industrial Organization has widely studied the effects of industry

[5] I use a differentiation measure from Sutton (2001) in order to classify these industries. The median of this measure is the threshold between non-differentiated and differentiated industries

Table 3.2: Advertising rankings of industries

Isic code	Isic label	All firms Rank	All firms Mean	Advertising firms Rank	Advertising firms Mean
2423	Pharmaceuticals, medicinal chemicals and botanical products	1	8.56	1	9.84
2424	Soap and detergents, cleaning and polishing preparations	2	6.77	3	8.12
1532	Starches and starch products	3	3.72	2	8.21
1554	Soft drinks; Mineral waters	4	3.21	5	4.61
1552	Wines	5	3.05	7	4.25
2813	Steam generators	89	0 .060	84	0.26
1911	Tanning and dressing of leather	90	0.051	91	0.10
2023	Wooden containers	91	0.041	89	0.16
3130	Insulated wire and cable	92	0.027	92	0.084
2412	Fertilizers and nitrogen compounds	93	0.013	93	0.036

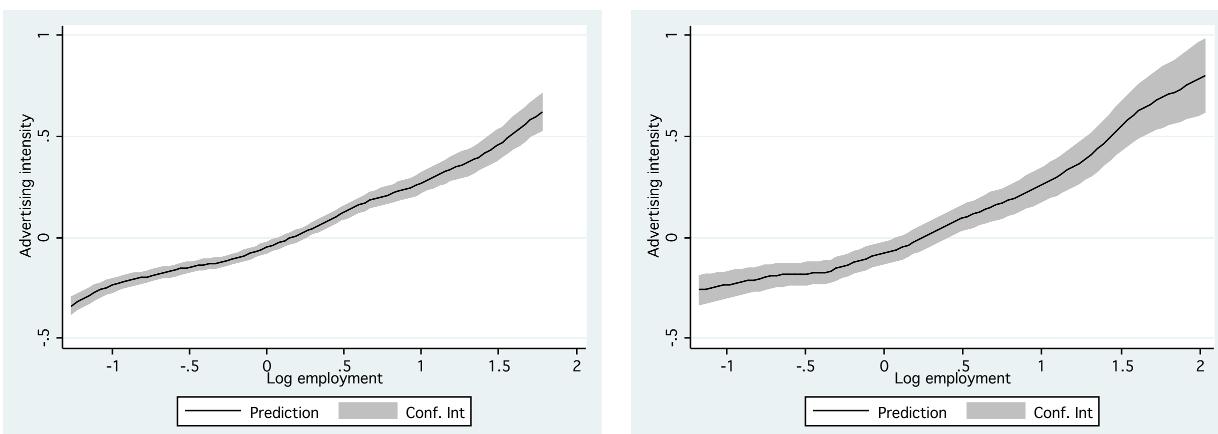
Notes: Average are computed among all firms first, and only among firms with positive advertising expenditures secondly. Only industries with at least five operating firms in 1996 are reported.

characteristics on advertising (see Bagwell (2005) for a survey). However, the main advantage of this dataset is to provide information on advertising at the plant level, which allows me to relate these expenditures to plant characteristics. Therefore, I will move to an analysis that focuses on within-industry heterogeneity, by comparing advertising intensities of firms operating in the same industry. I will return to industry-level characteristics in section 4, when trying to characterize the nature of this heterogeneity.

3.2.2 Stylized facts

Recent literature in international trade has emphasized the importance of within-industry heterogeneity to predict trade flows across nations. This is also true for recent models introducing advertising. Arkolakis (2010) predicts a larger growth rate for small exporters because they spend intensively more in advertising than large firms. However, Arkolakis (2010) does not have micro-level data on advertising in order to test his theory. The goal of this section is to look at this heterogeneity between small and large firms.

Heterogeneity across firm size Therefore, as a first test, we want to look at the link between the advertising intensity of a firm and its size in terms of number of employees. To avoid to make parametric restrictions on the econometric specification, we start by running nonparametric regressions[6] between these two variables: the advertising intensity, measured by the ratio in percentage of advertising expenditures over total sales, and the logarithm of the number of employees in the plant. Because we want to look at within-industry heterogeneity, we start by demeaning these two variables by the annual mean of the industry (ISIC Rev.3 at the 4 digit level). This will take into account industry and year effects. In figure 3.1(a), we present the results for a nonparametric regression between these two demeaned variables. We add, on the same figure, the confidence interval of the nonparametric regression in order to emphasize significant differences across firm size. Moreover, given the large number of plants that do not report any spending in advertising, we repeat this procedure for the sample of firms that report positive spendings in advertising.[7] The results for this restricted sample is presented in the figure 3.1(b).



(a) All firms.

(b) Only advertising firms.

FIGURE 3.1: Nonparametric regressions between advertising intensity and employment.

Notes: Advertising intensity is defined as the ratio of advertising expenditures over sales, expressed in percentages. Employment is measured by the number of employees. Both variables are demeaned using industry × year fixed effects. The Kernel function used is of type Epanechnikov and the bandwidth is set at 0.25.

[6]The Kernel function is Epanechnikov and the bandwidth equals 0.25

[7]Because we are using two different samples of firms, we demean our observations using each time the relevant sample. Therefore, deviations from zero with the sample of firms using advertising has to be seen as deviations from the average of this specific set of firms.

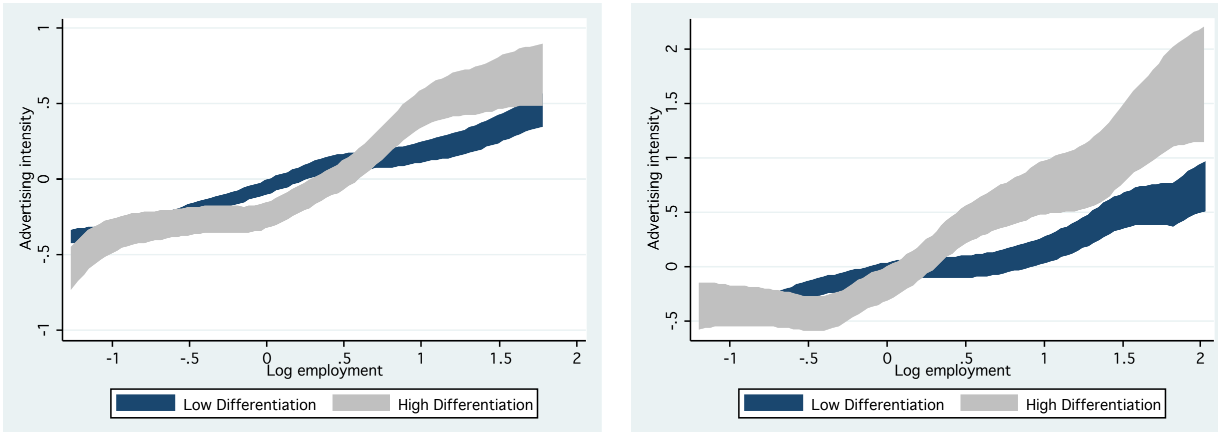
Figure 3.1 shows a strong positive correlation between the size of the firm and its advertising intensity. This is true when including all firms but also when only looking at firms using advertising. Therefore, when a firms gets larger, it will be more likely to use advertising, but will also spend a larger share of its sales in advertising. I will return later to the extent of this relationship, when using parametric regressions to quantify the elasticity between these two variables.

The role of vertical differentiation After showing a positive correlation between size and advertising intensity, I document the role played by the degree of vertical differentiation of the industry. To characterize this latter, we use a measure from Sutton (2001). This measure describes the degree of differentiation within an industry based on the levels of spendings, at the level of the industry, in advertising and R&D. I proceed as previously: I nonparametrically regress advertising intensity on the logarithm of the employment, but I do this separately for industries depending on their degree of vertical differentiation.[8] Results are presented in figure 3.2 for two samples: one using all firms (figure 3.2(a)) and one using only firms with strictly positive expenditures in advertising (figure 3.2(b)).

Figure 3.2 brings to light an interesting pattern: industries with a larger scope for differentiation also exhibits a stronger slope between advertising intensity and size. This does not strongly appear when considering all firms, but more explicitly when only considering plants with positive amount spent in advertising.

Therefore, the positive correlation between these two variables seems to be driven, at least partially, by the degree of vertical differentiation of the product. These two empirical facts cannot be predict by existing models of advertising with heterogeneous firms. Therefore, we want a model of advertising that generates a positive correlation between advertising intensity and size. We also want this correlation to be driven by the degree of differentiation of the product. In the section, I extend the model of Arkolakis (2010) in the following way: in addition to use advertising to inform new customers, I allow firms to use advertising to affect the perceived quality of their products. This view of advertising will generate the two empirical patterns presented above. In the next section, we describe this model and its empirical predictions.

[8]Industries with "low vertical differentiation" are those whose the Sutton index is below the 30th percentile. Industries described with "high vertical differentiation" are above the 70th percentile.



(a) All firms.

(b) Only advertising firms.

FIGURE 3.2: Nonparametric regressions for high and low degree of differentiation.

Notes: Advertising intensity is defined as the ratio of advertising expenditures over sales, expressed in percentages. Employment is measured by the number of employees. Both variables are demeaned using industry × year fixed effects. Differentiation is defined by the Sutton index (low differentiation for industries below the 30th percentile, high differentiation for those above the 70th. The Kernel function used is of type Epanechnikov and the bandwidth is set at 0.25.

3.3 The model

Firms use advertising in order to increase their market shares. It is a good way to inform consumers about the existence or the characteristics of their products, but also to affect their preferences by creating a reputation or an image for their goods. Researchers in Industrial Organization have studied for a long time these specific features of advertising. As early as Chamberlin (1933) is made a distinction between advertising as a way to convey information to consumers, and the use of advertising to alter consumers' taste. This led the literature to name "informative" advertising this first feature, which aims to bring information to consumers, versus "persuasive" advertising where marketing is used to affect potential consumers' will.

In this section, I describe a model where firms can invest in a type of advertising called "persuasive". I extend the model of Arkolakis (2010) which only focuses on informative advertising. In the latter, firms can adjust their extensive margin of consumers, the numbers of consumers aware of the existence of the product. In this model, they can, in addition, adjust their intensive margin by affecting the perceived quality of their own good. Consequently, the consumers preferences are a crucial part of this model and are defined in the following section.

3.3.1 Preferences

The demand system follows Verhoogen (2008) which describes, in a framework with international trade, the choice of the consumer as a discrete choice model: the problem of a given consumer i is to pick a specific variety for a good, among a set of different varieties. Among a set J_i, each variety is defined by its price p_j and its quality perceived by the consumer j q_{ij}. I assume each consumer has an indirect utility function where price and quality enter linearly. Formally, a consumer i picking the variety j will generate the following indirect utility function.

$$U_{ij} = q_{ij} - \sigma p_j + \varepsilon_{ij} \tag{3.1}$$

where σ is a demand parameter describing the price elasticity of the demand. Following the discrete choice literature, I add a variety specific error term ε_{ij} in order to generate some heterogeneity in the consumer's choices.

Assuming that the idiosyncratic shock ε_{ij} is distributed according to an extreme value distribution, we can express the probability that a consumer i chooses good j, given a set J_i of available varieties, as the following:

$$P(j|J_i) = \frac{\exp(q_{ij} - \sigma p_j)}{\sum_{s=1}^{J_i} \exp(q_{is} - \sigma p_s)} \tag{3.2}$$

From this equation that describes the individual demand from a consumer i for each variety, we are interested in obtaining the aggregate demand each firm faces. First of all, I denote L_j the number of consumers that are aware of the existence of the product j, such that it is part of their set of available products J_i.

Moreover, in order to keep the problem simple, we need two assumptions. First, instead of keeping track of all the individual perceived quality, I assume that each consumer has the same perceived quality q_j for a given good j. Therefore, the quality q_j of a product can be seen as the average valuation of the product among consumers. Secondly, I need to assume that the number of available varieties is constant among consumers. I will return later to the mechanisms generating this set of available varieties for each consumer. But this condition will be satisfied when assuming that consumers are equally reachable by firms.[9]

[9] Moreover, I will show later that monopolistic competition will make this variable irrelevant in the choices of firms, and the individual decisions

Assuming these aggregate values of q_j and J, the aggregate demand function for a variety j can be written as follows:

$$D(q_j, p_j, L_j) = L_j \frac{\exp(q_j - \sigma p_j)}{\sum_{s=1}^{J} \exp(q_s - \sigma p_s)} \tag{3.3}$$

Given this demand function, I can now look at the decisions of the producers, introducing in particular the use of advertising by firms.

3.3.2 Supply side

Given the demand function previously described, the operating profit from a product j will be :

$$\pi(q_j, p_j, L_j, c_j) = D(q_j, p_j, L_j)(p_j - c_j) = L_j \frac{\exp(q_j - \sigma p_j)}{\sum_{s=1}^{J} \exp(q_s - \sigma p_s)} (p_j - c_j) \tag{3.4}$$

The profit of a firm will therefore depend on these four variables : the average perceived quality of its product q_j, its price p_j, the number of consumers who can potentially buy the product L_j and its marginal cost c_j. In order to define the problem of a firm, I need to specify which of these variables are endogenous and result from the choice of the firm. I will assume for simplicity that each variety is produced by a single firm and that marginal costs are identical across firms regardless of the quality of their product. Consequently, heterogeneity across firms is only characterized by their quality. This is a version of the Melitz (2003) framework where quality is the source of heterogeneity across firms, as described in Baldwin and Harrigan (2011). However, a producer will be able to decide the price p_j of its product, as well as its number of potential customers L_j and its average perceived quality q_j.

As it is often assumed in frameworks with monopolistic competition, firms will not take into account their impact on the aggregate objects in their profit function (the denominator of the demand function in my case). As a consequence, the optimal price charged by a firm will only depend on the marginal cost of the firm, and the parameters of the demand functions. Indeed, the optimal price charged by a producer will be $p_j = c + \frac{1}{\sigma}$: firms will charge a mark-up over their marginal cost, this mark-up being decreasing with the elasticity of demand. I can therefore substitute this equation in the profit function, such that we have:

$$\pi(q_j, L_j) = L_j \frac{\exp(q_j)}{\sum_{s=1}^{J} \exp(q_s)} \frac{1}{\sigma} \tag{3.5}$$

The choice of q_j and L_j by the producer will occur through the existence of a marketing technology, allowing the firm to affect the number of consumers aware of the existence of their products L_j, but also the average perceived quality of their good q_j. We describe this technology in the next section.

3.3.3 Informative and Persuasive Advertising

In this section, we extend the idea of Arkolakis (2010) which introduces informative advertising as a new margin for the firm. He inserts, in a framework with heterogeneous firms, the possibility for firms to adjust their set of potential consumers by spending in an advertising technology described as informative. In my model, I allow the firms to also affect the perceived quality of their product. Therefore, in addition to spending money in informative advertising, they can also use a persuasive advertising technology to affect the valuation of their products by consumer. Formally, while Arkolakis (2010) allows firms to endogenously choose L_j, I assume they can also affect q_j through advertising.

The use of advertising by the firms will occur through the existence of two types of advertisements the firm can randomly send on the market. A first type of ad will make the consumer aware of the existence of the product. A second type will increase its valuation of the product, in the case that the consumer is already aware of its existence. We denote γ the valuation increase, such that aware consumers receiving this ad will end up with a valuation $q'_j = q_j + \gamma$ of the product j. Consequently, this parameter γ will reflect the degree of differentiation of this product by advertising.

Therefore, I need to introduce some notations to describe how the firms can affect L_j and q_j. First of all, following Arkolakis (2010) again, I define as n_{1j} the share of consumers aware of the existence of the product j. Obviously, n_{1j} will be between 0 and 1 such that I directly obtain $L_j = n_{1j}L$, L as being the size of the population in the economy. Secondly, I define as n_{2j} as the share of aware consumers for which their valuation of the products j will increase. Consequently, the population of the economy can be divided into three categories. A share $1 - n_{1j}$ will not know the product j, a share $n_{1j}(1-n_{2j})$ will know the product but will evaluate it as the valuation q_j. Finally, a share $n_{1j}n_{2j}$ will be aware of its existence and will consider its quality as $q_j+\gamma$. These two variables n_{1j} and n_{2j} will summarize the choice of advertising by firms, n_1 describing the informative component and n_2 the persuasive one.

Once setting the endogenous variables of the model, we need to rewrite the profit functions according to these variables. As previously emphasized, I assume that the firm makes decisions according to a single aggregated quality of its product. Because only a share n_{1j} of the population is aware of the product, the average valuation $\bar{q}_j$ of the product j on the market, conditional on being aware of it, is:

$$\bar{q}_j = \frac{1}{n_{1j}}\left(n_{1j}(1-n_{2j})q_j + n_{1j}n_{2j}(q_j+\gamma)\right) = q_j + \gamma n_{2j} \tag{3.6}$$

Consequently, I can rewrite the profit function defined in equation (3.5) to introduce these endogenous variables:

$$\pi(n_{1j}, n_{2j}) = n_{1j}L\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\frac{1}{\sigma} \tag{3.7}$$

Naturally, the profit function will be increasing in both variables n_1 and n_2. It is also important to notice that whereas n_1 enters linearly in the profit function, it will not be the case of n_2 whose impact will depend on the quality-elasticity of the profit function. This difference will allow us to obtain different predictions for the correlation between size and advertising intensity: while the informative function of advertising can only enter linearly in the profit function, the perceived quality of the product will enter in a convex way in the profit of the firm. This will become significant when we will look at the empirical predictions of this model.

Advertising costs The use of this advertising technology is not free. I therefore need to introduce cost functions related to the numbers of advertisements produced in order to reach the corresponding shares n_1 and n_2 of consumers. Because we have two types of advertising, and consequently two types of ads, I will define separate cost functions for each purpose : $F_1(n_1, L)$ will be the cost of reaching a fraction n_1 of consumers, while $F_2(n_1, n_2, L)$ will be the cost associated with upgrading the valuation of a fraction n_2 when the share of informed consumers is n_1. These cost functions can be seen as the costs generated by sending a large enough number of ads to inform a fraction n_1

of consumers of the existence of the product, and increase the valuation of a fraction n_2 of these informed consumers. Based on this advertising technology, I can make several restrictions on the functional form of these costs functions.

First of all, I will assume that the cost functions are homogeneous relative to the size of the economy L. Therefore, it will be twice as expensive to reach shares n_1 and n_2 of customers in an economy that is twice the size. An easy way to see this is to consider an advertisement as a flyer, that can only reach one person or a given number of persons.

Secondly, the cost function for persuasive advertising will be independent from n_1, even though n_2 is a fraction of n_1. To understand this, we must imagine the firm is willing to reach a given share n_2 by randomly sending ads in the population. The impact of n_1 will be double: first, a large n_1 will increase the probability to reach a consumer who is already aware of the existence of the product. Secondly, because n_2 is a fraction of n_1, a large n_1 will increase the number of ads that have to be sent to persuade a fraction n_2. Formally, for a given n_1 and n_2, the probability to increase the valuation of a consumer is $n_1 \times (1-n_2)$. Because the generated increase in n_2 will be equal to $1/n_1$, the marginal increase in n_2 by an additional ad will be $n_1 \times (1-n_2) \times \frac{1}{n_1} = (1-n_2)$. Consequently, the cost function for persuasive advertising $F_2(n_1, n_2, L)$ will be independent from n_1.

Finally, I will assume that these costs are increasing and convex in n_1 and n_2. This assumption is both supported by the data and economic intuition. Bagwell (2005), in an article surveying the literature, cites several papers finding empirical evidences of diminishing returns of advertising. But this assumption is also motivated by economic intuition; therefore, it is not surprising that first models of advertising entail diminishing returns. Butters (1977) for example, describes a model where ads are randomly sent to mailboxes. In this setup, the probability to inform a previously unaware consumers is decreasing with the share of consumers already aware of the existence of the product. Similarly, in a model where the firms could target specific consumers, marginal cost associated with advertising should be increasing since firms will start by targeting the closest customers.[10]

[10] A simple illustration would be a geographical model where consumers are located throughout space. If advertising costs depend on the distance to the consumers, firms will start by informing close consumers and will later go further, such that marginal advertising costs are increasing.

Consequently, the characteristics of these costs functions can be summarized as follows :

$$
\begin{aligned}
F_1(n_1, L) &\equiv L \times F_1(n_1) \qquad \text{with} \qquad F_1'() > 0 \quad \text{and} \quad F_1''() > 0 \\
F_2(n_1, n_2, L) &\equiv L \times F_2(n_2) \qquad \text{with} \qquad F_2'() > 0 \quad \text{and} \quad F_2''() > 0
\end{aligned}
\tag{3.8}
$$

In order to obtain closed form solutions for the model, I will set $F_1(n_1) = c_a \frac{1}{\alpha} n_1^{\alpha}$ and $F_2(n_2) = c_a \frac{1}{\beta} n_2^{\beta}$, with α and β larger than 2, and c_a as the cost parameter for advertising. I will come back to the importance of these functional forms when describing the empirical predictions of this model. Moreover, I will assume that β is larger than $\gamma + 1$, γ being the parameter of vertical differentiation. This will allow me to reject corner solutions when the firms endogenously set their effort in advertising.

Optimal advertising The overall profit of the firms, including advertising costs, will therefore be:

$$
\begin{aligned}
\Pi(n_{1j}, n_{2j}) =& \pi(n_{1j}, n_{2j}) - LF_1(n_1) - LF_2(n_2) \\
=& L n_{1j} \frac{\exp(q_j + \gamma n_{2j})}{\sum_{s=1}^{J} \exp(\bar{q}_s)} \frac{1}{\sigma} - L \frac{c_a}{\alpha} n_{1j}^{\alpha} - L \frac{c_a}{\beta} n_{2j}^{\beta}
\end{aligned}
\tag{3.9}
$$

Taking the first order conditions relative to n_1 and n_2, I obtain the following choice of n_1 and n_2:

$$
\begin{aligned}
n_{1j}^{*} &= \left[\frac{\exp(q_j + \gamma n_{2j})}{\sum_{s=1}^{J} \exp(\bar{q}_s)} \frac{1}{c_a \sigma} \right]^{\frac{1}{\alpha - 1}} \\
n_{2j}^{*} &= \gamma^{\frac{1}{\beta - 1}} \left[\frac{\exp(q_j + \gamma n_{2j})}{\sum_{s=1}^{J} \exp(\bar{q}_s)} \frac{1}{c_a \sigma} \right]^{\frac{\alpha}{(\alpha-1)(\beta-1)}}
\end{aligned}
\tag{3.10}
$$

For analytical simplicity, n_2 also appears in the right hand side of these equations. This is convenient because the entire object $\frac{\exp(q_j + \gamma n_{2j} - c)}{\sum_{s=1}^{J} \exp(\bar{q}_s - c)}$ describes the market shares of the firms on its set of aware consumer. Moreover, I can show that the solutions n_1 and n_2 for this system are unique.[11] Also,

[11] Looking at the equation defining the optimal choice of n_{2j}, both sides are strictly increasing in n_{2j}. Because n_2 is defined between 0 and 1, we can show that the right-hand side is larger than 0 at $n_2 = 0$. Moreover, for a large enough value of c_a, the right hand side is lower than one at $n_2 = 1$. A sufficient condition is therefore that the derivative of the left-hand side is larger than the one of the right-hand side. A sufficient condition for this is that, if these derivatives are equal et some point n_2, they can be so only at an unique point. This can be easily shown since the derivative of the right-hand side ($\gamma^{\frac{\beta}{\beta-1}} \frac{\alpha}{(\alpha-1)(\beta-1)} \left[\frac{\exp(q_j + \gamma n_{2j})}{\sum_{s=1}^{J} \exp(\bar{q}_s)} \frac{1}{c_a \sigma} \right]^{\frac{\alpha}{(\alpha-1)(\beta-1)} - 1}$) is monotonic in n_2 and the derivative of the left-hand side is 1. This proves the uniqueness of the solution.

I carefully describe in the appendix C.1 the optimization problem of the firms leading to these solutions. In particular, I emphasize the role of the constraint imposed on the parameters when setting $\gamma < \beta - 1$.

Following these optimal choices of n_1 and n_2, two main characteristics emerge. First, both are increasing with the quality of the product, and decreasing with the cost of the firms. More generally, they are increasing with the average profit of the firm. Therefore, in a framework with heterogeneous firms, most productive firms - defined in a general way - will spend more on advertising. The intuition is straightforward: since these firms have higher marginal revenue, they are, consequently, willing to reach a higher marginal cost of advertising. However, we will show later than the advertising intensity - the share of sales spent on advertising - is more difficult to link with the size and the productivity of the firm.

Secondly, we can note that the elasticity of advertising expenditures relatively to the average profit of the firm is higher for n_2 than n_1. Indeed, when looking at the amount spent in advertising, n_1^α will grow at a rate $\frac{\alpha}{\alpha-1}$ while n_2^β will grow at a rate $\frac{\alpha\beta}{(\alpha-1)(\beta-1)}$. This is a crucial point that explains why the use of persuasive advertising will generate the positive correlation between advertising intensity and size. This effect comes from the fact that informative advertising only allows a firm to increase the set of potential consumers. Therefore, when a firm gets bigger, the marginal benefit of advertising is constant - equal to a new potential consumer, while advertising marginal costs increase, because this new consumer is more difficult to reach. However, this will not be the case for persuasive advertising. Indeed, the marginal return of persuasive advertising will be also increasing with the size of the firm - because a change in the perceived quality is exponential. That is why the introduction of an advertising of type persuasive will generate an increasing advertising intensity with the size of the firm.[12]

3.3.4 Empirical predictions

I extended the model from Arkolakis (2010) in order to match the empirical patterns presented in the previous section. The advertising intensity of a firm is increasing with its size, and this positive

[12] In his theoretical appendix, Arkolakis (2010) introduces persuasive advertising. However, he shows that this feature of advertising is homothetic to his initial version with informative advertising. The reason is that he normalizes the quality of the product such that it enters linearly in the profit function of the firm. In my situation, persuasive advertising affects the outcome of my model because the quality of the product enters in a convex way in the profit function.

correlation is stronger in industries with a large scope for vertical differentiation. Because I added a persuasive component of advertising, I can now look at the empirical predictions of this type of advertising, but also the predictions from the informative component of advertising.

The two components of advertising, informative and persuasive, will indeed generate opposite predictions about the link between advertising intensity and size at the firm-level. To describe this link, we need to derive the advertising intensity of a firm A_j, defined as $A_j = A_{1j} + A_{2j} \equiv \frac{F_1(n^*_{1j})}{R_j} + \frac{F_2(n^*_{2j})}{R_j}$, R_j as the total revenue of the firm. From the problem of the firm, we also have $R_j = n^*_{1j} \frac{\exp(q_j + \gamma n_{2j})}{\sum_{s=1}^{J} \exp(\bar{q}_s)} \left(\frac{1}{\sigma} + c\right) L$. We therefore obtain the following expressions for the advertising intensity optimally chosen by a firm:[13]

$$\begin{aligned} A_j &= \frac{\frac{c_a}{\alpha} n^{*\alpha}_{1j} L}{n^*_{1j} \frac{\exp(q_j + \gamma n_{2j})}{\sum_{s=1}^{J} \exp(\bar{q}_s)} \left(\frac{1}{\sigma} + c\right) L} + \frac{\frac{c_a}{\beta} n^{*\beta}_{2j} L}{n^*_{1j} \frac{\exp(q_j + \gamma n_{2j})}{\sum_{s=1}^{J} \exp(\bar{q}_s)} \left(\frac{1}{\sigma} + c\right) L} \\ &= \frac{1}{\alpha(1+\sigma c)} + \frac{1}{\beta} \left(\frac{1}{c_a}\right)^{\frac{1}{\beta-1}} \left[\frac{\gamma}{1+\sigma c}\right]^{\frac{\beta}{\beta-1}} \left[\frac{R_j}{L}\right]^{\frac{1}{\beta-1}} \end{aligned} \tag{3.11}$$

This result shows different patterns for each type of advertising. Advertising intensity from the expenditures in informative advertising appears to be only dependent from structural parameters of the model. Moreover, these parameters are industry-specific and consequently, do not vary across firms. Therefore, this would predict a constant intensity of advertising between firms within a same industry. However, we can see that the advertising intensity coming from the persuasive type of advertising is directly related with the sales of the firms. More precisely, a firm would increase its advertising intensity with its size at a rate $\frac{1}{\beta-1}$. As emphasized in the previous section, this effect comes from the argument that while a saturation effect shows up when we only consider advertising as informative, this is not true with persuasive advertising. The marginal returns of persuasive advertising increase with the size of the firms, such that they compensate for the increasing marginal costs of advertising.

Moreover, the coefficient of vertical differentiation γ has a positive impact on the advertising intensity heterogeneity within an industry. Therefore, goods with a high degree of vertical differentiation will imply a steeper link between the size of a firm and its advertising intensity. Indeed,

[13] Details for these computations are in the appendix C.2

when taking the derivative of the advertising intensity relative to the logarithm of sales, we obtain:

$$\frac{\partial A_j}{\partial log R_j} = \frac{1}{\beta(\beta-1)} \left(\frac{1}{c_a}\right)^{\frac{1}{\beta-1}} \left(\frac{\gamma}{1+\sigma c}\right)^{\frac{\beta}{\beta-1}} \left(\frac{R_j}{L}\right)^{\frac{1}{(\beta-1)}} \tag{3.12}$$

In the appendix C.3, I show how this result is dependent from the demand system used. I show that the existence of a correlation between revenue and advertising intensity requires persuasive advertising. When we only consider informative advertising, we obtain a constant advertising intensity regardless of the demand system specified.[14] Moreover, only a few assumptions are required in order to obtain a positive relationship between advertising intensity and size when adding persuasive advertising.

In addition to the type of demand system used, another important assumption has been made when specifying the cost functions of advertising. In my model, I chose a specific type of cost functions in order to obtain closed-form solutions for the link between advertising intensity and size. However, this choice has important implications on the predictions of my model. Moreover, they are different from cost functions previously used in Arkolakis (2010) for instance. In the next section, I show how the conclusions of my model are not affected by alternative choices of cost functions.

The importance of the cost function In order to describe the role played by the functional form used for the cost function of advertising, we describe a similar problem without putting any restriction on the cost function. Therefore, we will be able to derive sufficient and necessary conditions on the cost functions, to predict the positive correlation between the advertising intensity of a firm and its size. Taking the first order conditions, we have:

$$\begin{aligned} L\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\frac{1}{\sigma} - LF_1'(n_{1j}) = 0 \\ \gamma L n_{1j}\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\frac{1}{\sigma} - LF_2'(n_{2j}) = 0 \end{aligned} \tag{3.13}$$

[14] As long as this demand system generates constant mark-up between firms

Using these two first order conditions, we can rewrite the advertising intensities as:

$$\begin{aligned} A_{1j} &= \frac{LF_1(n_{1j})}{n^*_{1j}\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\left(\frac{1}{\sigma}+c\right)L} = \frac{F_1(n_{1j})}{n_{1j}F'_1(n_{1j})(1+\sigma c)} \\ A_{2j} &= \frac{LF_2(n_{2j})}{n^*_{1j}\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\left(\frac{1}{\sigma}+c\right)L} = \frac{\gamma F_2(n_{2j})}{F'_2(n_{2j})(1+\sigma c)} \end{aligned} \tag{3.14}$$

Since we can show that the optimal choices for n_{1j} and n_{2j} are strictly increasing with the size of the firm, we can easily derive conditions for which the advertising intensity of a firm will be increasing with its size, by taking the derivatives of the previous formulas relatively to n_{1j} and n_{2j}. We thus obtain:

$$\frac{\partial A_1}{\partial R} > 0 \qquad \Longleftrightarrow \qquad \frac{F'_1(n_1)}{F_1(n_1)} > \frac{F''_1(n_1)}{F'_1(n_1)} + \frac{1}{n_1} \tag{3.15}$$

$$\frac{\partial A_2}{\partial R} > 0 \qquad \Longleftrightarrow \qquad \frac{F'_2(n_2)}{F_2(n_2)} > \frac{F''_2(n_2)}{F'_2(n_2)} \tag{3.16}$$

Looking at these two conditions, what is important is that the relative slope of the cost function is large enough in comparison with its degree of convexity. Intuitively, if marginal costs of advertising increase too fast, then large firms will not invest as much in advertising, and therefore we will observe a decreasing level of advertising intensity with its size. Importantly, the previous condition will be more likely to hold when looking at expenditures in persuasive advertising. Since $\frac{1}{n_1} > 1$, equation (3.16) is more likely to hold in comparison with equation (3.15). Therefore, a positive correlation between size and advertising intensity is more likely to be predicted in a model of persuasive advertising rather than one of informative advertising.

Previously in this paper, we chose a specific functional form for the cost function in order to obtain a closed form solution for the advertising intensity. However, because we have derived equivalent conditions, we are now able to predict a theoretical relationship between size and advertising intensity for any type of function - as long as it is increasing and convex. In particular, we are interested in the specific function derived in Arkolakis (2010). As previously mentioned, this paper describes a model of informative advertising with heterogeneous firms. More interestingly, Arkolakis (2010), using a formulation from Butters (1977), derives a cost function of advertising based on micro-foundations. Even if this functional form doesn't allow us to obtain a closed form solution for the advertising problem, we can look at its prediction in terms of the advertising intensity / size correlation. This function,[15] defined for a parameter $\delta > 0$, is of the following form:

$$f(n) = \begin{cases} \frac{1-(1-n)^{1-\delta}}{1-\delta} & \text{if} \quad \delta \neq 1 \\ -\log(1-n) & \text{if} \quad \delta = 1 \end{cases} \tag{3.17}$$

Using this functional form, we can show that equation (3.15) does not hold, while equation (3.16) holds for certain values of parameters. Details of these proofs are in appendix C.4. This means that using this functional form, we would predict a negative correlation between size and advertising intensity in a model of informative advertising,[16] and an undetermined relationship in a model of persuasive advertising.[17]

More generally, this emphasizes the fact that a model of informative advertising with heterogeneous firms would predict a negative or null correlation between the size of the firm and its advertising intensity. The functional form of Arkolakis (2010) is an example of this. At my knowledge, I could not find a convex and increasing function that satisfies the constraint (3.15).[18] Consequently, the assumptions made in our model regarding the cost function appears to be an extreme case, since it generates an absence of correlation between advertising intensity and size.[19] In a different framework, Kugler and Verhoogen (2012) derives the optimal amount spent in advertising by a firm. The context is however different because it assumes a strict complementarity between the price of the input used and the amount invested in advertising. Nevertheless, their model predicts a constant advertising intensity across heterogeneous firms.

Therefore, introducing persuasive advertising in a model with heterogeneous firms is a method to generate an increasing advertising intensity with the size of the firm, a prediction that could not be obtained when limiting the model to informative advertising. Moreover, I have shown that, when driven by persuasive advertising, this positive correlation is emphasized by a parameter describing

[15] We refer to Arkolakis (2010) to obtain details on the construction of the function

[16] This explains why the model developed in Arkolakis (2010) predict a larger elasticity of sales for small firms following a reduction in marginal costs: the growth rate is larger in small firms in this model because they spend a larger share of their sales in advertising.

[17] Using an alternative function from Arkolakis (2010), $F(n) = \frac{1}{1-n} - 1$, we can show that equation (3.15) will never old, while equation (3.16) is equivalent to $n < \frac{1}{2}$

[18] However, I did not manage to establish a proof for a contradiction between an increasing and convex function defined on $[0, 1]$ and equation (3.15)

[19] Using the cost functions from the previous section, we can check that equation (3.16) holds while (3.15) holds with an equality.

the scope for vertical differentiation of the product. In the next section, I return to the data in order to precisely test my theory.

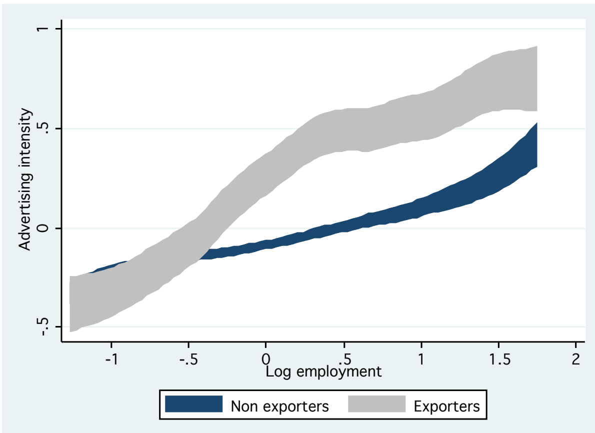
3.4 Testing the theory

The model presented in section 3 of this paper, shows that a model of informative advertising cannot, under few assumptions, predict a positive correlation between a firm's advertising intensity and its size. It then showed that introducing persuasive advertising could generate this positive relationship. However, this argument is not exclusive. In this section, we will show that the data first provides specific support to a model of persuasive advertising, and secondly rejects alternative mechanisms. In order to do so, we rely on the facts that our dataset provides information about firms that operate within different industries. Using cross-sectional variations between industries, we can identify the industries for which the theory predicts a stronger correlation between advertising intensity and size.

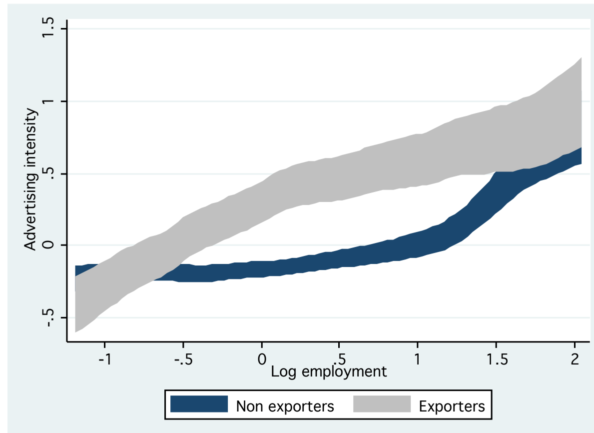
3.4.1 Correlation between Advertising Intensity and Size

We start this section by examining more precisely the empirical pattern exposed in section 2. We have shown that, within a defined industry, larger firms report larger advertising intensity than smaller firms. Overall, it appears that this positive correlation brings support to a model of persuasive advertising that would predict a positive link. It is important to note that I developed my theoretical model in a framework where firms can only serve one market, and therefore optimally choose to invest in advertising according to this unique market. In order to be certain that this correlation holds when looking at firms operating within a single market, I reproduce the similar procedure, but distinguish between exporting and non exporting firms. We know from recent trade literature that exporters are on average larger than other firms (see Bernard, Jensen, and Lawrence (1995) for instance). If, for reasons that we explore below, exporters spend larger shares of their sales in advertising, they could generate the observed positive correlation between size and advertising intensity.

Figure 3.3 aims to explore this possibility. We regress non parametrically the advertising intensity of the firm on its size.[20] Figure 3.3(a) provides this for all plants whereas figure 3.3(b) only provides it for plants with positive advertising expenditures.



(a) All firms.



(b) Only advertising firms.

FIGURE 3.3: Nonparametric regressions for exporters and non exporters.

Notes: Advertising intensity is defined as the ratio of advertising expenditures over sales, expressed in percentages. Employment is measured by the number of employees. Both variables are demeaned using industry $\times$ year fixed effects. Exporters are defined as plant selling to at least one foreign country. The Kernel function used is of type Epanechnikov and the bandwidth is set at 0.25.

We can see from figure 3.3 that the overall pattern is unchanged. Exporters and non exporters both record a larger advertising intensity when their size increases. It appears that exporters are more intensive in advertising - as it was observed in the summary statistics. But this higher intensity does not appear to be consistently larger for all exporters, since very small and very large exporters have similar level of advertising as non exporters.

In order to measure more precisely this link between advertising intensity and size, we reproduce these regressions using parametric assumptions. Table 3.3 presents several parametric specifications summarizing the findings from the previous nonparametric regressions. Regression (1) uses the entire sample of plants while regression (2) only uses plants with positive advertising expenditures. Finally, specifications (3)-(4) are similar to the first two, but add a alternate set of coefficients for exporting firms.

[20]The demeaning of the variables is not done separately for exporters versus non exporters. Only the two different samples (all firms and only advertising firms) are demeaned separately.

TABLE 3.3: Regressions between advertising intensity and size

	Advertising intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Employment)	0.35***	0.37***	0.26***	0.22***	0.26***	0.21***
	(0.027)	(0.041)	(0.018)	(0.030)	(0.037)	(0.046)
Exporting firm			-0.46**	-0.75***		
			(0.15)	(0.20)		
Log(Emp)×Export			0.16***	0.24***		
			(0.043)	(0.054)		
Multi Product					-0.23	-0.51*
					(0.15)	(0.22)
Log(Emp)×Multi					0.098*	0.17**
					(0.043)	(0.057)
N	59398	29095	59398	29095	59398	29095
R^2	0.298	0.333	0.299	0.335	0.298	0.333
Restrict. Sample	No	Yes	No	Yes	No	Yes

Notes: Standard errors in parentheses, are clustered at the industry× year level. All regressions include industry×year fixed effects. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These results are consistent with the figures previously shown. The advertising intensity of a firm increases with its size. Because specifications (1) and (2) provide similar results, this positive correlation holds if we only consider an intensive increase of the advertising effort. Indeed, specification (2) only considers firms with a positive effort in advertising. Quantitatively, using specification (1), we can say that when doubling its size, a firm will observe an increase of its advertising intensity of 0.35 percentage points.

Moreover, if exporters have a higher correlation between size and advertising intensity, this does not explain the entire correlation between these two variables. Specifications (3) and (4) show this because the result is robust when we allow a specific set of coefficients for exporting firms. However, It might seem surprising that the dummy for exporters is negative. This implies that small exporters spend less in advertising than small non exporters. However, This result is consistent with the theory. If you assume that an exporter is equivalent to two smaller firms, with similar cost and product but selling to two different markets, then it should behave similarly to smaller firms in terms of advertising. Therefore, the exporter should select a smaller advertising intensity, consistent with its average revenue on a market. What the theory does not explain however, is why exporters increase their advertising intensity at an higher rate than non exporters. The purpose of this paper is not to explain this pattern, but we can still provide some intuitions. Recent literature in trade has emphasized the role of quality to reach foreign markets. In particular, Verhoogen (2008) shows how Mexican producers upgrade their product following a trade liberalization. The situation of Chilean producers is probably similar to that of Mexican firms. Exporters may have a higher product quality, explaining their activity abroad, and explaining a larger advertising intensity. Because we see that only middle-size exporters have larger advertising intensities, this could describe plants, whose production is mainly destined for abroad. This would explain a high quality and therefore a high advertising intensity, in a medium-sized firm. Another potential explanation would come from specific demand characteristics of exporters. If foreign consumers have a lower price-elasticity of their demand, or are more receptive to persuasive advertising, my model predicts a steeper slope between advertising intensity and size.

3.4.2 The role of vertical differentiation

In the previous section, I have shown that the correlation between size and advertising intensity increases with the degree of vertical differentiation of the product. Recall the equation (3.12) from above:

$$\frac{\partial A_j}{\partial log R_j} = \frac{1}{\beta(\beta-1)} \left(\frac{1}{c_a}\right)^{\frac{1}{\beta-1}} \left(\frac{\gamma}{1+\sigma c}\right)^{\frac{\beta}{\beta-1}} \left(\frac{R_j}{L}\right)^{\frac{1}{(\beta-1)}}$$

We can see that this derivative is increasing in γ, a parameter describing the ability for a firm to vertically differentiate its product through advertising. Therefore, the theory predicts that industries with goods with a high ability of vertical differentiation should generate an higher heterogeneity in terms of advertising intensity and therefore a larger correlation between size and advertising intensity in this industry. I will test this theory by exploiting variations across industries.

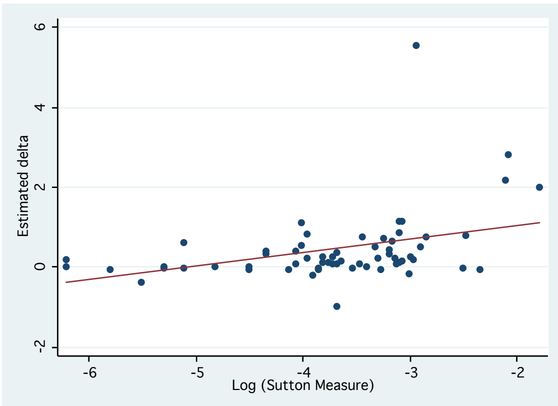
Therefore, a first step consists of estimating, separately for each industry, the correlation between advertising intensity and size. I do this by estimating, for each industry separately, the specifications (1) and (2) in Table 3.3. I use both the entire sample of plants and the restricted sample, only containing firms who report positive expenditures of advertising. I therefore obtain coefficients $\hat{\delta}_{1i}$ and $\hat{\delta}_{2i}$ for each industry - related to specifications (1) and (2) in Table 3.3 - that estimates the derivative $\frac{\partial A_j}{\partial logR_j}$.

A second step will aim to relate these estimates with the degree of vertical differentiation of the industry. In order to do so, we rely on the recent literature in International Trade and Industrial Organization to measure the potential for vertical differentiation at the industry-level. Sutton (2001) provides such a measure that has been recently exploited in order to characterize the degree of vertical differentiation of industries (see Kugler and Verhoogen (2012) in particular). This index describes the scope for vertical differentiation, based on measures of R&D and advertising expenditures at the industry level in the US. Because this measure is using information about advertising, we need to be careful about the possibility for this variable to be mechanically related with our advertising/size relationship measured at the industry-level. However, our estimates of $\frac{\partial A_j}{\partial logR_j}$ describe the slope of the relationship between advertising intensity and size. By definition, they will be orthogonal to the intercepts in our regressions, this intercept being the parameter describing the importance of advertising expenditures in the industry.

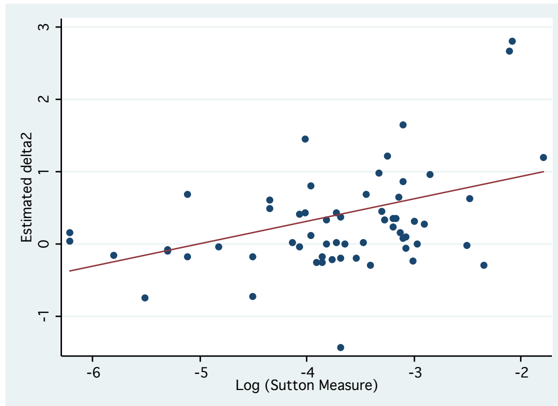
A more recent measure of vertical differentiation is from Khandelwal (2010). By setting a structural model of demand at the product level, Khandelwal (2010) is able to estimate a quality measure of the imports to the US, depending on their country of origins. Once this quality is inferred, he can measure the quality ladder for a specific product, by comparing the highest quality with the lowest quality. Therefore, this gap between these qualities arguably is a good proxy for the vertical differentiation at the product-level.

Figure 3.4 presents the results of this procedure. The left axis displays the estimated δs while the bottom axis describes our measure of vertical differentiation. The top panels used the Sutton index as a measure of vertical differentiation, while the bottom ones describe the same figure using the quality ladder measure. I show results that use estimates from the entire sample (panels on the left-hand side) and the restricted sample (on the right side). Moreover, I add a line on each figure representing the least squares regression between the two variables. Because this regression is based on aggregated measures, I weight each observation at the industry-level by the total employment in this industry.

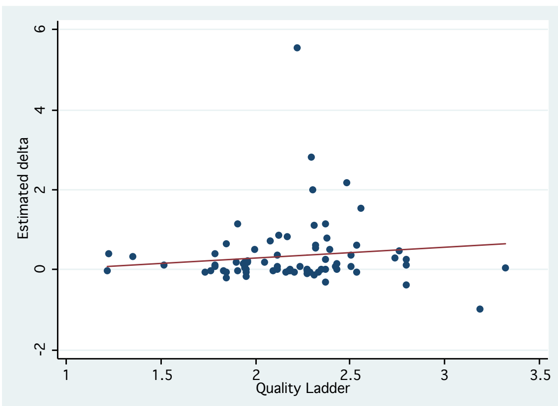
In figure 3.4 we see a strong correlation between the estimated advertising/size relationship and the measure of vertical differentiation by Sutton. This relationship is statistically significant at standard thresholds. However, the measure of quality ladder from Khandelwal (2010) does not



(a) All firms and Sutton measure.



(b) Only advertising firms and Sutton measure.



(c) All firms and quality ladder measure.

(d) Only advertising firms and quality ladder measure.

FIGURE 3.4: Scatterplots between estimated advertising/size relationship and vertical differentiation.

appear to be significantly related with our coefficients estimated at the industry-level. In order to inspect this relationship further, I rerun the regression estimated in the previous sections, allowing a heterogeneous slope between advertising intensity and size, depending on the degree of vertical differentiation of the industry. In order to do so, I interact the logarithm of employment with the measures of vertical differentiations (previously demeaned). This procedure has the advantage of avoiding problems in the estimation of standard errors in a two-stage procedure. Results are presented in Table 3.4 for the entire sample, and for the restricted sample, which only includes firms with positive advertising expenditures.

TABLE 3.4: Advertising intensity/Employment relationship with interacted variables

	Advertising intensity					
	All firms			Only advertising firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Employment)	0.35***	0.40***	0.34***	0.37***	0.40***	0.35***
	(0.027)	(0.025)	(0.032)	(0.041)	(0.038)	(0.049)
Sutton× log(Emp)		9.55***			11.0***	
		(0.90)			(1.03)	
Ladder× log(Emp)			0.21***			0.27***
			(0.051)			(0.080)
N	59398	46881	44214	29095	22845	23310
R^2	0.298	0.333	0.308	0.333	0.366	0.343

Notes: Standard errors in parentheses, are clustered at the industry×year level. All regressions include industry×year fixed effects. Both interacted variables are centered around their mean before interaction. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results support the theory in all specifications: a high scope for vertical differentiation boosts the relationship between advertising intensity and the logarithm of employment. This is true when considering both the comprehensive and the restricted samples, but also for each measure of vertical differentiation. The ability of a product to be vertically differentiated increases the profitability for firms to use persuasive advertising, generating a stronger correlation between size and advertising intensity.

Even though these last results have shown that a larger vertical differentiation generates a steeper slope between advertising intensity and size, it appears necessary to show that this correlation cannot be generated by other mechanisms than the one described in my theoretical model. In particular, I consider three alternative explanations that could generate a similar patterns: the role of horizontal differentiation first, a dynamic extension of the model secondly, and finally a heterogeneity in terms of cost instead of quality. In the next section, I describe these three mechanisms and show how they are not consistent with the observed data.

3.4.3 Alternative explanations

Horizontal versus Vertical Differentiation The Sutton index is based on recorded spendings in R&D and Advertising at the industry-level. Therefore, besides capturing the scope for vertical differentiation, it also measures the degree of horizontal differentiation within an industry. Following Kugler and Verhoogen (2012) that is confronted with the same issue, I will use two measures of horizontal differentiation to test if they are similarly related with the advertising/size link at the industry-level. First of all, I will use the Rauch (1999) index, measuring the degree of differentiation of a product. In addition, I will use a modified version of the Gollop and Monahan (1991) index, modified by Bernard and Jensen (2007). This index describes the similarity between input shares of plants operating in the same industry.

With these different measures of differentiation at the industry-level in hand, we can proceed as previously described, by adding interacted terms. This will show how these characteristics affect the slope between advertising intensity and the logarithm of employment. Results are displayed in Table 3.5.

We can see from table 3.5 that neither of these two measures of horizontal differentiation has a positive impact on the slope between advertising intensity and size. The Gollop and Mohanan index has a significant but negative impact on this slope. This result is robust when we restrict the sample to firms that spend positive amounts in advertising. Therefore, horizontal differentiation cannot explain why the Sutton measure is positively correlated with the advertising/size relationship. This confirms the point made earlier regarding the role of vertical differentiation in generating more heterogeneity across firms in their advertising intensity.

Table 3.5: Advertising/size relationship: Vertical vs Horizontal differentiation

	Advertising intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Employment)	0.40***	0.34***	0.41***	0.42***	0.39***	0.42***
	(0.025)	(0.032)	(0.033)	(0.035)	(0.027)	(0.041)
Sutton× log(Emp)	9.55***				9.65***	
	(0.90)				(0.90)	
Ladder× log(Emp)		0.21***				0.32***
		(0.051)				(0.075)
G-M× log(Emp)			-0.55***		-0.024	-0.61***
			(0.16)		(0.081)	(0.17)
Rauch× log(Emp)				-0.0067	-0.11**	0.10*
				(0.051)	(0.038)	(0.052)
N	46881	44214	46881	46881	46881	34478
R^2	0.333	0.308	0.305	0.304	0.333	0.315

Notes: Standard errors in parentheses, are clustered at the industry×year level. All regressions include industry×year fixed effects. All interacted variables are centered around their mean before interaction. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Survival probability and advertising investment When thinking about advertising expenditures, one could think of a dynamic model where firms invest each period in advertising in order to receive benefits today or in the future. In this framework, another hypothesis could explain why small firms report low advertising intensity relatively to large firms: an heterogeneity in term of survival rates.

To illustrate this, we should consider only two periods, the firm selecting its stock of consumers n_{1j} in the first period and receiving a quality shock on q_j in the second period. Due to the existence of fixed costs of production, the firm will stop producing in the second period if its quality is below a threshold $\bar{q}$. Formally, the value of the firm is

$$\begin{aligned} V(n_{1j}, q_{j1}) =& Ln_{1j} \frac{\exp(q_{j1})}{\sum_{s=1}^{J} \exp(q_{s1})} \frac{1}{\sigma} - L\frac{c_a}{\alpha} n_j^{\alpha} - f \\ &+ \beta E \left[\max \left\{ Ln_{1j} \frac{\exp(q_{j2})}{\sum_{s=1}^{J} \exp(q_{s2})} \frac{1}{\sigma} - f; 0 \right\} |q_{j1} \right] \end{aligned} \tag{3.18}$$

Imposing a stochastic structure for the process of quality, we can obtain a closed form solution for the expected profit in period 2. Assuming $q_{j2} = q_{j1} + u_j$ where $u_j \to N(0, v)$, we obtain the optimal choice of n_{1j}, given the initial quality of the product, and the associated advertising intensity of the firm :

$$\begin{aligned} n^*(q_{i1}) &= \left[\frac{\pi(q_{i1}) \left(1 + \beta \exp\left(\frac{v^2}{2}\right) \Phi\left(\frac{q_{i1} - \bar{q}}{v} + v\right)\right)}{c_a} \right]^{\frac{1}{\alpha - 1}} \\ A(q_{i1}) &= \frac{1}{\alpha(1 + \sigma c)} + \frac{\beta \exp\left(\frac{v^2}{2}\right) \Phi\left(\frac{q_{i1} - \bar{q}}{v} + v\right)}{\alpha(1 + \sigma c)} \end{aligned} \tag{3.19}$$

We can see that we obtain the similar result as previously in the absence of endogenous exit. If the probability of exit is zero for each firm, we obtain a constant advertising intensity across firm. However, when there is a possibility of endogenous exit, firms close to the quality threshold will reduce their investment in advertising because of a non-zero probability to lose their capital accumulated in the second period. Consequently, if we see the stock of consumers as an asset that persists over time, the existence of endogenous exit can generate higher advertising intensity for larger firms relative to smaller firms. And this pattern has been generated with a model of informative advertising without any use of persuasive advertising.

Therefore, if vertically differentiated industries appear to have heterogeneous exit rates across their firms, this mechanism could explain the statistical relationships observed earlier. In order to show that this is not found in the data, I employ the following strategy: I start by measuring in each industry how the probability of exit is related to the size of the firm. To do so, I estimate a logistic model explaining the survival probability in the next period by the size of the firm (measured by the logarithm of employment). Therefore, the coefficient obtained for this variable measures the heterogeneity of survival rate across firms in this industry : the bigger this coefficient, the larger is the survival rate for large firms relative to small firms. Having this measure of selection at the industry-level in hand, I can use it as an interacted variable to measure how it affects the slope between advertising intensity and size. I can then check that the introduction of this interacted variable does not affect the patterns previously presented. Results are displayed in table 3.6 using, once again, the full and restricted sample of firms.

The introduction of this new control variable does not affect the results previously presented. First, the introduction of this selection variable seems to contradict the mechanism of dynamic

TABLE 3.6: The role of heterogeneous survival rates.

	Advertising intensity					
	All firms			Only advertising firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Employment)	0.35***	0.40***	0.34***	0.37***	0.40***	0.35***
	(0.027)	(0.025)	(0.032)	(0.041)	(0.039)	(0.048)
Selection×log(Emp)	-0.055*	-0.072	-0.032	-0.17**	-0.33*	-0.12*
	(0.024)	(0.084)	(0.022)	(0.056)	(0.14)	(0.049)
Sutton× log(Emp)		9.50***			10.8***	
		(0.91)			(1.06)	
Ladder× log(Emp)			0.21***			0.27***
			(0.051)			(0.080)
N	59398	46881	44214	29095	22845	23310
R^2	0.298	0.333	0.308	0.333	0.367	0.343

Notes: Standard errors in parentheses, are clustered at the industry×year level. All regressions include industry×year fixed effects. All interacted variables are centered around their mean before interaction. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

advertising. The interacted variable Selection×log(Emp.) appears to have a slightly negative effect on the advertising/size relationship. Secondly, it does not affect the positive signs obtained for the variable of vertical differentiation.

Overall, we can reject a mechanism of dynamic advertising as explaining the observed positive correlation between the size of a firms and its advertising intensity.

Cost heterogeneity versus Quality heterogeneity When developing my theoretical model, I have assumed that the only heterogeneity across firms comes from heterogeneous quality of their product. Therefore, I have opted for a quality version of the framework described in Melitz (2003), instead of a cost or productivity version of this model. Looking back to our model of advertising previously exposed, a heterogeneity in cost generates a heterogeneity in advertising intensity. Recall from equation (3.11) that in a simple model of informative advertising, we can write the advertising intensity of a firm, whose cost is c_j, as $A_j = \frac{1}{\alpha(1+\sigma c_j)}$. Therefore, if firms are larger due to lower costs, they would be more intensive in advertising since A_j is decreasing in c_j. Because we have shown that this relationship is stronger in vertically differentiated industries, this would indicate that the cost advantage of large firms should be larger in those industries. However, Kugler and Verhoogen (2012) have recently shown that, within an industry, output and input prices are increasing with the size of the firm on average. Moreover, this correlation is stronger in industries with a large scope for vertical differentiation. Therefore, this would predict a negative correlation between size and advertising intensity, even more so in vertically differentiated industries. These predictions are strongly rejected by the empirical evidences presented above. We can therefore reject cost heterogeneity as being the mechanism explaining this heterogeneity in terms of advertising intensity.

3.5 Concluding remarks

The data brings to light a clear pattern : firms spend a larger share of their sales when they are bigger. This is even more the case in industries where there is a larger scope for vertical differentiation. In this paper, I built on Arkolakis (2010) a model of advertising with heterogeneous firms, that is consistent with these observed patterns. A necessary condition to predict a positive correlation between advertising intensity and size is to allow firms to affect the valuation of their products through advertising, what the literature in Industrial Organization describes as persuasive advertising.

The use of an advertising of type persuasive by the firms opens the door of numerous theoretical predictions, that could explain empirical patterns unexplained so far, such as the dispersion in prices across destinations. As highlighted in the introduction, by affecting consumer preferences, persuasive advertising could explain the existence of heterogeneity in term of prices, that cannot be accounted by models using productivity as a source of heterogeneity. Literature about firms' behaviors has often put productivity as the main determinant of firms activity. Similarly, R&D was a way for a firm to affect this productivity. Recent literature has shown the importance of quality, and developed models of endogenous quality through the choice of inputs (see Kugler and Verhoogen (2012) for instance). However, a model in which consumers' preferences are endogenously affected by the choice of the firm has not been developed yet in a context with heterogeneous firms.

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Appendix A

Appendix for Chapter 1

A.1 Constructions of the samples

The dataset used in the paper is initially disaggregated at the monthly level. From this raw dataset, a number of steps are implemented to improve the reliability and consistency of the data. First, I describe the operations implemented for the first empirical exercise, that uses a wide set of products. Then, I describe the procedures implemented to obtain the final sample used in the structural estimation.

A.1.1 Data appendix for the reduced-form exercise

I implement two important steps to prepare the data for the regressions displayed in the reduced-form exercise. First, I clean outliers and product categories that do not provide a meaningful and consistent unit of count across years. Second, I correct for the partial-year bias.

Cleaning and harmonization I make three different operations to clean the dataset from potential outliers or measurement errors.

- First, I use the algorithm from Pierce and Schott (2012) and Van Beveren, Bernard, and Vandenbussche (2012) to account for changes in product categories at the eight digit level. This algorithm allows me to obtain categories that are consistent across the sample years (1996-2010).

- Second, I drop product categories that meet one of the following criteria:

- the counting unit is changing across years.
- the counting unit is not identical within the category (because of the previous step, the current product category can contain eight digit categories with different units).
- the counting unit is weight. The reason for this exclusion relies on the use of weight for many categories as the default unit. While this can be a relevant unit for some goods, it is often used for product categories that gather non homogeneous product.

- Finally, because unit values, constructed as export values divided by quantities, are a source of measurement errors, I winsorize them at the eight-digit product category$\times$country$\times$year level. Specifically, I set at the values of the 5th and 95th percentiles the prices that are beyond these two thresholds.

Correction for partial-year bias As described in Berthou and Vicard (2015) and Bernard, Massari, Reyes, and Taglioni (2014), a firm will sell less in average during its first calendar year as exporter. This is because calendar years do not necessarily match the beginning of the exporting activity. In order to correct for this potential bias, I reconstruct the dataset to align calendar exporting years of each exporter. The idea is to define a new year for each spell of export, setting the first month of this year as representative of a regular year, and constructing exporting spells based on this new starting month.

Specifically, the following procedure is applied to each firm-destination-product triplet: for the earliest observation in 1996, if no observation is seen in 1995, a new spell is defined: the month of this first flow is probabilistically drawn based on the number of flows observed during the following 12 months. Then, the year is set to 1996 or 1997 depending on whether the initial month is earlier or later than July. The following observations are adjusted accordingly to preserve the duration between monthly export flows, as long as there is no discontinuity in the exporting activity according to the newly defined calendar years. In case of discontinuity, the next observation becomes a new reference point, and the same procedure is applied for this observation and the following ones.

Once this adjustment is implemented, I aggregate the data at the yearly-level. Specifically, I sum values exported within each newly created calendar year at the firm-product-category level. Moreover, I obtain yearly prices using an export-weighted average of monthly prices. In case of missing prices, I assume a weight of zero for this observation. If this observation is the only observation within a firm-destination-product- year combination, I drop all the observations within the firm-destination-product triplet.

This procedure leaves me with sales and prices measured at the firm-product-destination-year level, with no missing observation in prices, and adjusted for the existence of partial-year of exporting.

A.1.2 Data appendix for the structural estimation

The procedure to clean the data for the structural estimation is different than the reduced-form exercise. I describe in this subsection the choice of the wine industry and the set of destinations I use for implementing my estimation. Then, I describe the cleaning procedure implemented on the wine producers and provide summary statistics on the final sample of firms used in the estimation.

Wine industry

The decision to implement this estimation on wine exporters relies on two constraints. First of all, I study the entry decision made at the firm level. This level of analysis is explained by the fact that brands and reputation are often defined by the firm that produces the good. Therefore, this requires to study firms that display a small level of heterogeneity in terms of goods. A car producer for instance, that also exports car pieces, or engines for other vehicles, is difficult to analyze as a single-product firm. However, a wine producer mostly export wines, and specifically bottles of wine, whose prices are easy to define, and aggregate at the firm level. For these reasons when defining my sample, I will exclusively use wine producers that do not export any other goods outside of wine. A large share of the trade in wine is made by wholesalers who export other types of items, and for which the study at the level of the firm is irrelevant. In addition to this homogeneity constraint, my estimation procedure requires enough firms which export to several destinations. As a major exporting industry from France, the wine industry meets both of these conditions: a large number of exporters, exporting a precisely defined good.

In addition to imposing restrictions on the set of firms included in the final sample, I only use a restricted set of destinations.

Selection of destinations

I select 15 different destinations on which I analyze the behaviors of French exporters. These destinations have been selected among the 20 most popular destinations for wine exports from France, excluding countries with large import/export platforms such as Denmark and Singapore, while reflecting some heterogeneity in terms of location. Moreover, I divide these destinations in three groups, for which I will estimate different entry and fixed costs of exporting, as well as different trend in aggregate demand. The list of these destinations can be found in table A.1.

TABLE A.1: List of destination countries included in the structural sample

	Group 1 *Europe*		**Group 2** *Americas*	**Group 3** *Asia/Oceania*
Great-Britain	Germany	Belgium	(Brazil)	Australia
Netherlands	Italy	Spain	Canada	China
Ireland	Sweden	Switzerland	United States	Japan

Note that I do not include Brazil in the structural sample. The observations related to this destination will be used in the out-of-sample exercise and are excluded so that it does not affect the estimation procedure.

Aggregation

Because the estimation is conducted at the firm-destination-year level, it is necessary to aggregate the sales and quantities exported across products exported by the firm. The choice of the wine industry is crucial here since bottles of wines are quantities that can be easily aggregated. An industry producing differentiated goods would have made this aggregation less straightforward.

The aggregation of prices and sales are the following:

$$p_{fdt} = \sum_{h=1}^{H_{fdt}} w_{fhdt} \frac{s_{fhdt}}{q_{fhdt}} \qquad \text{with} \quad w_{fhdt} \equiv \frac{s_{fhdt}}{\sum_h s_{fhdt}}$$

$$s_{fdt} = \sum_{h=1}^{H_{fdt}} s_{fhdt}$$

where H_{fdt} is the number of 8-digit observations for each firm-destination-year triplet. Moreover, note that there is a certain number of missing quantities in the data. Therefore, I assign a weight w_{fhdt} equal to zero to the observations that have quantities or values exported equal to one or zero. When this observation is the only one at the firm-destination-year level (no other product is sent to this market by this firm this year), I dropped all the observations related to this firm from the sample.

Partial-year bias

Similar to the sample used in the reduced form exercise, I will correct for the partial-year bias, by redefining the entry months of all entering exporters. As a consequence, I shift all the subsequent flows to maintain the same sequence in the exports of the firm. Therefore, exports during the first year will look similar to the subsequent years of exporting.

Cleaning

I clean the data to avoid the potential existence of outliers in prices. In order to do so, I run a regression of the logarithm of prices, on sets of time, destinations and firm-specific dummies. Formally, I estimate

$$\log p_{fdt} = \alpha_f + \beta_d + \gamma_t + \varepsilon_{fdt}$$

and I define $\log \hat{p}_{fdt} = \hat{\alpha}_f + \hat{\beta}_d + \hat{\gamma}_t$. Therefore I can flag prices that deviate from these predicted prices. In particular, I consider outliers prices that deviate from a factor 2 of its predicted value ($p_{fdt} > 2\hat{p}_{fdt}$ or $p_{fdt} < 1/2\hat{p}_{fdt}$). As a cleaning procedure, I dropped all the observations of a firm which has at least one outlier among its observations.

Finally, a last criterion for a firm to be included in the final sample is based on the number of observations. Many firms export one year to one market during the sample period, and this does not provide enough information to analyze their exporting behavior. Therefore, I only keep firms that recorded at least 15 exporting events. Note that with 14 destinations and 14 years of data, the maximum number of observations by a given firm is 196. This selection process could present a problem as it is likely to affect the estimates of entry and fixed costs of exporting, by only looking at successful firms. However, this procedure will tend to select firms that survive several years, rather than short-lived exporters: as a consequence, it will tend to go against the theory of consumer accumulation that can accommodate small and short-lived exporters relative to the standard model.

Final sample

Once these cleaning steps were implemented, I randomly sampled 200 firms among the set of firms available. Moreover, in order to have enough exporters that have activity in Brazil, and conduct the out-of-sample predictions exercise, I required that 100 of these 200 firms have some exporting activity in Brazil during the sample period.

TABLE A.2: Description of the sample used in the structural estimation

Statistics:	*pc5*	*median*	*pc95*	*mean*	N
# observations per firm	15	36.5	97.5	44.2	200
av. # destinations per firm-year	1.65	3.64	8.29	4.16	2118
av. # years per firm-destination	2.5	5	9.5	5.29	1626

Table A.2 provides information regarding the number of observations provided by the sampled firms, as well as the number of destinations they export to in an average year. One can see that the firms selected are relatively large, with a minimum number of export episodes equal to 15 by the sampling procedure. However, the median firm only records 29 export episodes, while the maximum number of episodes in the dataset is 196 (14×14). Moreover, they are relatively diversified in terms of destinations since the median firm exports to 3.11 destinations in an average year.

In order to inspect how this sampling procedure affects the trajectories of the exporters, I replicate the regressions on age dummies I perform in section 1.2. Figure A.1 reports the results of these regressions for sales, prices and survival rates.[1] The patterns of sales and prices are very similar to the ones observed using the comprehensive sample: sales appear to increase in the early years, with the an average growth rate of 30 percent the first year. Meanwhile, the variations in prices are small and insignificant across ages. However, we can see that the survival rates in the structural sample are larger than the ones displayed in the exhaustive data. While the survival rate

[1] Table A.3 provides the tables related to these regressions.

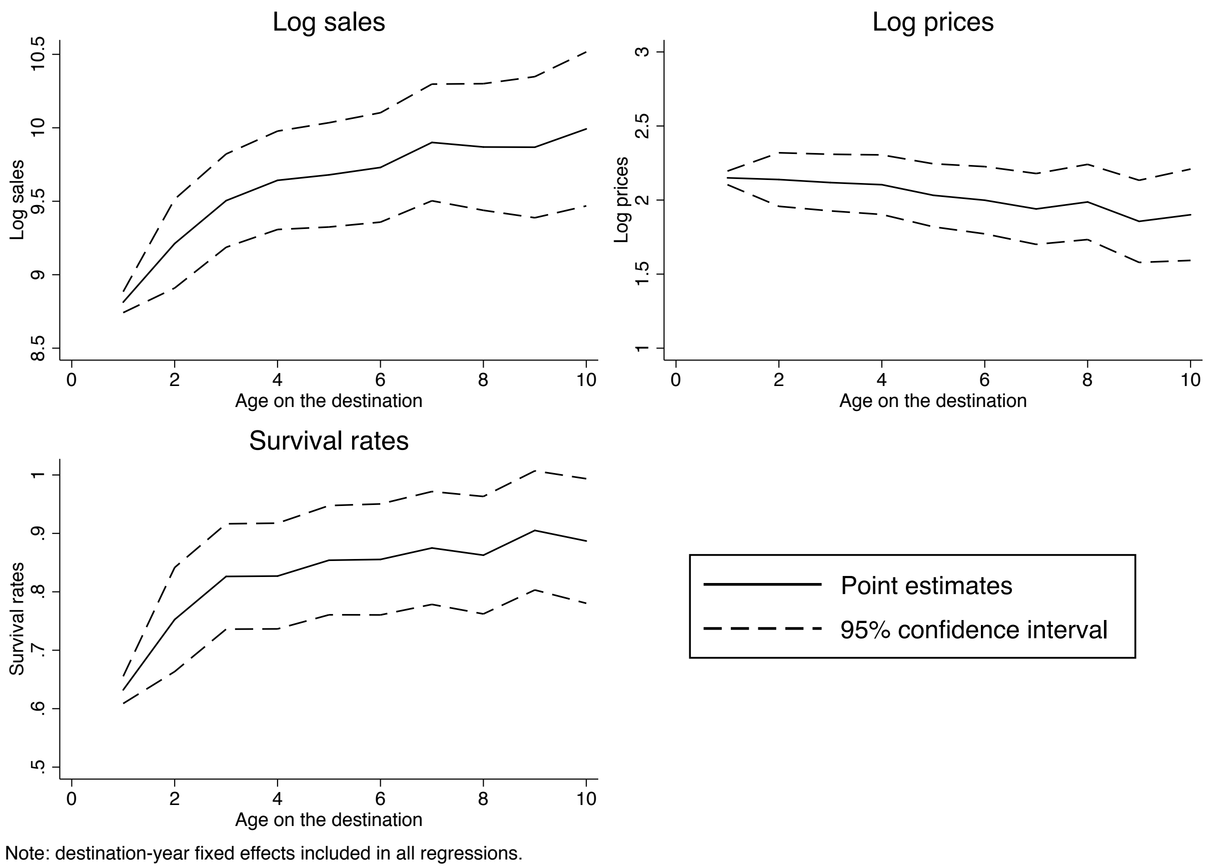


Figure A.1: Sales, prices and survival rates across ages (Wine producers)

Notes: The figure reports the average log sales, log prices and survival rates of wine producers in a destination at different ages. The estimates are obtained from the regression of these dependent variables on a set of age dummies and destination×year fixed effects. The age in a destination is defined as the number of years a firm has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors estimates clustered at the firm-destination level.

was close to 35 percent in the full sample, it is around 60 percent in this restricted sample. This arises because of the requirement made during the selection of exporters: because the estimation procedure requires firms with several observations, this tends to eliminate firms with very large attrition rates that do not records many episodes of exporting activity. Note that this difference in survival rates between exhaustive and restricted samples will play against the story I develop in this paper. Large attrition rates will be consistent with a story that emphasizes strong dependence in demand rather than an important role for sunk costs of entry.

Table A.3: Age regressions using the structural sample

	No fixed effects			Year x destination fixed effects		
	(1) Log sales	(2) Log prices	(3) Survival rates	(4) Log sales	(5) Log prices	(6) Survival rates
Age 2	0.407***	-0.0199	0.126***	0.366***	-0.0343*	0.122***
	(0.0344)	(0.0165)	(0.0163)	(0.0358)	(0.0161)	(0.0165)
Age 3	0.662***	-0.0254	0.174***	0.627***	-0.0712***	0.171***
	(0.0439)	(0.0221)	(0.0172)	(0.0457)	(0.0214)	(0.0177)
Age 4	0.860***	-0.0295	0.187***	0.849***	-0.0886**	0.188***
	(0.0526)	(0.0270)	(0.0188)	(0.0548)	(0.0270)	(0.0196)
Age 5	0.902***	-0.0200	0.243***	0.898***	-0.0948**	0.231***
	(0.0619)	(0.0336)	(0.0191)	(0.0658)	(0.0334)	(0.0200)
Age 6	0.993***	-0.0339	0.255***	1.006***	-0.111**	0.242***
	(0.0690)	(0.0392)	(0.0204)	(0.0760)	(0.0400)	(0.0216)
Age 7	1.006***	-0.0706	0.246***	1.010***	-0.151**	0.234***
	(0.0791)	(0.0437)	(0.0225)	(0.0886)	(0.0466)	(0.0240)
Age 8	1.053***	-0.0767	0.259***	1.056***	-0.160**	0.249***
	(0.0935)	(0.0497)	(0.0242)	(0.102)	(0.0562)	(0.0266)
Age 9	1.333***	-0.147**	0.318***	1.298***	-0.248***	0.306***
	(0.100)	(0.0519)	(0.0214)	(0.117)	(0.0645)	(0.0234)
Age 10	1.403***	-0.128*	0.309***	1.405***	-0.240***	0.311***
	(0.116)	(0.0568)	(0.0243)	(0.138)	(0.0704)	(0.0280)
Age 11	1.281***	-0.105	0.268***	1.309***	-0.227**	0.274***
	(0.126)	(0.0632)	(0.0352)	(0.158)	(0.0830)	(0.0368)
Age 12	1.455***	-0.105	0.380***	1.576***	-0.252*	0.389***
	(0.170)	(0.0774)	(0.0108)	(0.201)	(0.100)	(0.0225)
Age 13	1.199***	-0.0416	0.199	1.279***	-0.196	0.191
	(0.232)	(0.118)	(0.117)	(0.269)	(0.146)	(0.126)
Age 14	1.608**	-0.429*	.	1.708**	-0.678**	.
	(0.558)	(0.208)	.	(0.589)	(0.254)	.
Constant	8.751***	2.034***	0.620***	8.762***	2.073***	0.623***
	(0.0314)	(0.0214)	(0.0108)	(0.0349)	(0.0216)	(0.0111)
Observations	7525	7525	6821	7525	7525	6821
R^2	0.092	0.002	0.060	0.175	0.172	0.121

Notes: Firm x destination clustered standard errors between parentheses. * p<0.05, ** p<0.01, *** p<0.001

A.2 Additional age regressions

In this section, I describe alternative specifications to look at the correlation between sales or prices and age in an export market.

A.2.1 Additional specifications

Firm-destination-product fixed effects

A natural way to control for heterogeneity across firms, which could drive the correlation across ages, is to include firm-destination-product fixed effects such that the regression becomes

$$X_{fpdt} = \sum_{\tau=1}^{10} \delta_\tau \mathbb{1}(\text{age}_{fpdt} = \tau) + \mu_{pdt} + \mu_{fpd} + \varepsilon_{fdt}.$$

However, including this set of fixed effects will make it impossible to identify a trend in prices across ages. To understand why, first consider a sample of firms on a given market *pdt*. Because of the market-level fixed effect, their average price is normalized to zero. Now consider this same set of firms a year later. If none of these firms exited, it means that their average price is normalized to zero. More generally, the fact that age is a treatment that is homogenous across firms makes the identification of any trend impossible. However, because in the data, some firms will exit the market, it means that this treatment is not entirely symmetrical across firms, such that some identification is possible. But this identification will entirely rely on firms that exit and re-enter, with an age that will be one in the future. As a consequence, the inclusion of this set of fixed effects will not control for selection, but instead will make the entry and exit of firms the only source of identification. Figures A.2 and A.3 report the results of this specification for sales and prices. As we can see, even sales are not increasing with age with this specification.

Identification across destinations

An alternative way to identify an increase in sales and prices across age is to compare similar products sold to different destinations, and, therefore, having different export experiences. In terms of specifications, it means including a set of firm-product fixed effects such that the variation identifying the changes with age occurs across destinations. However, this specification is also potentially

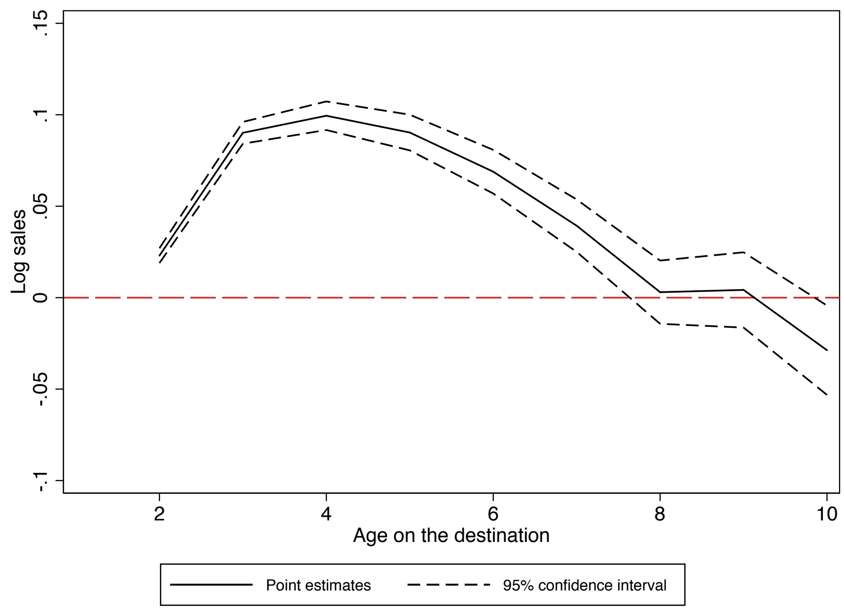


FIGURE A.2: Sales across export ages, within variation

Notes: The figure reports the cumulative growth of sales compared to age one, of a firm-product category pair in a destination at different ages. The regression uses logarithm of sales as dependent variable, and includes product category×destination×year and firm×product category×destination fixed effects. The age in a destination is defined as the number of years a firm-product pair has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors clustered at the firm-product-destination level.

problematic since it compares old destinations, for which the firms has chosen to export first, and young destinations that have been chosen more recently by the firm. Therefore, it is not clear that the age across these flows are the only differences. To verify this claim, I run the following specification and display the results for sales and prices in figures A.4 and A.5.

$$X_{fpdt} = \sum_{\tau=1}^{10} \delta_\tau \mathbb{1}(\text{age}_{fpdt} = \tau) + \mu_{pdt} + \mu_{fp} + \varepsilon_{fdt}$$

We can see that all figures maintain the increasing in trends of sales and prices, even though price regressions are not as significant as in the main specification. However, one can see that the endogenous sorting of the destinations seem to play a role in shaping this relationship: using a constant set of firms tends to increase the growth in sales. Therefore, it is difficult to imagine that this specification accounts for the dynamic selection across age, but instead could pick up the endogenous sorting across destinations.

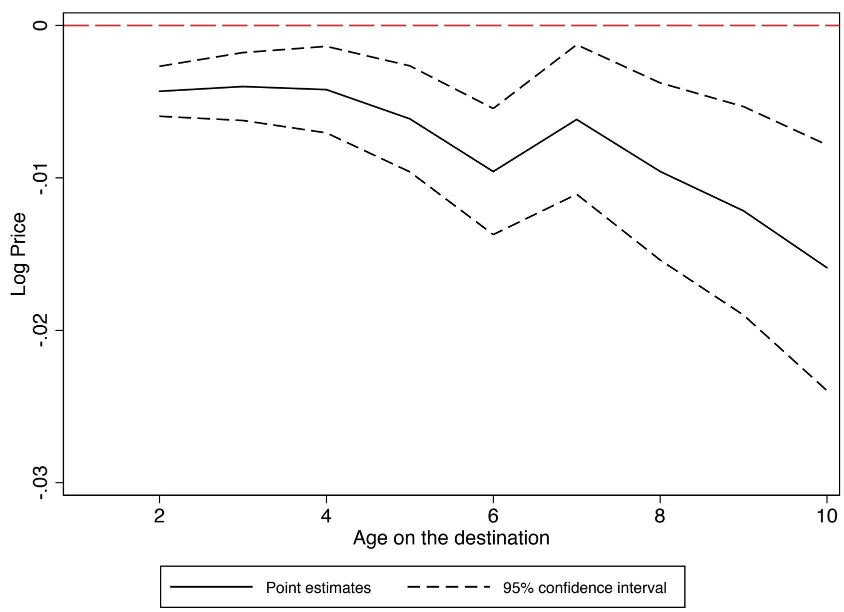


Figure A.3: Prices across export ages, within variation

Notes: The figure reports the cumulative growth of prices compared to age one, of a firm-product category pair in a destination at different ages. The regression uses logarithm of sales as dependent variable, and includes product category×destination×year and firm×product category×destination fixed effects. The age in a destination is defined as the number of years a firm-product pair has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors clustered at the firm-product-destination level.

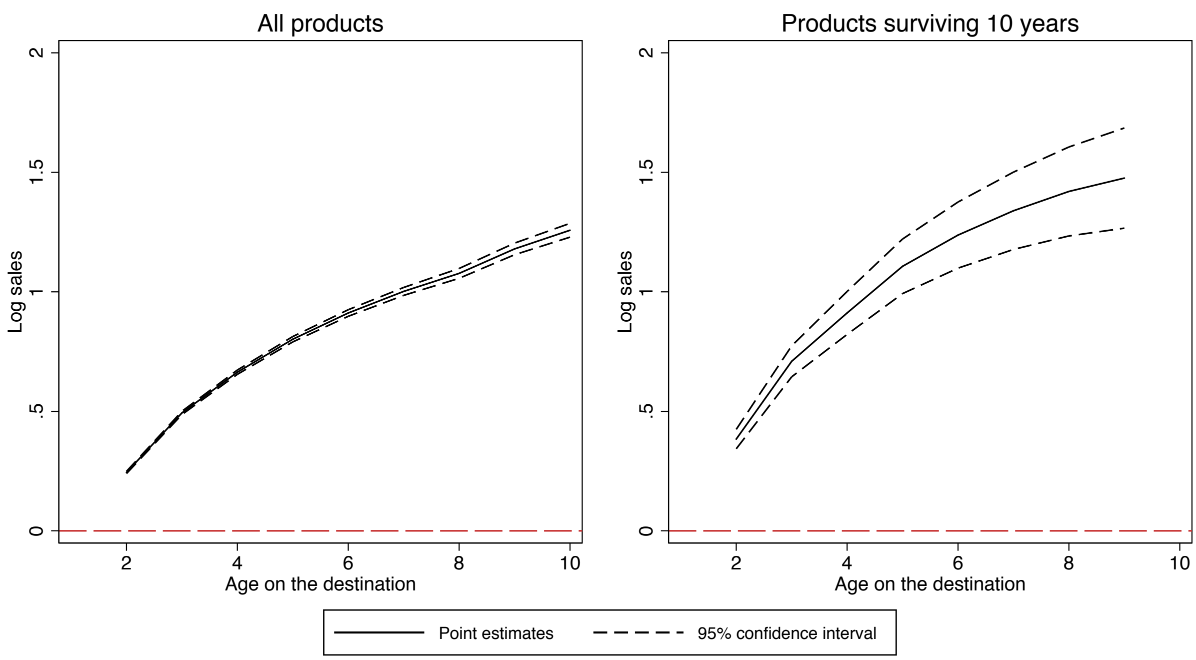


Figure A.4: Sales across export ages, across destinations

Notes: The figure reports the cumulative growth of sales compared to age one, of a firm-product category pair in a destination at different ages. The regression uses logarithm of sales as dependent variable, and includes product category×destination×year and firm×product category fixed effects. The age in a destination is defined as the number of years a firm-product pair has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors clustered at the firm-product level.

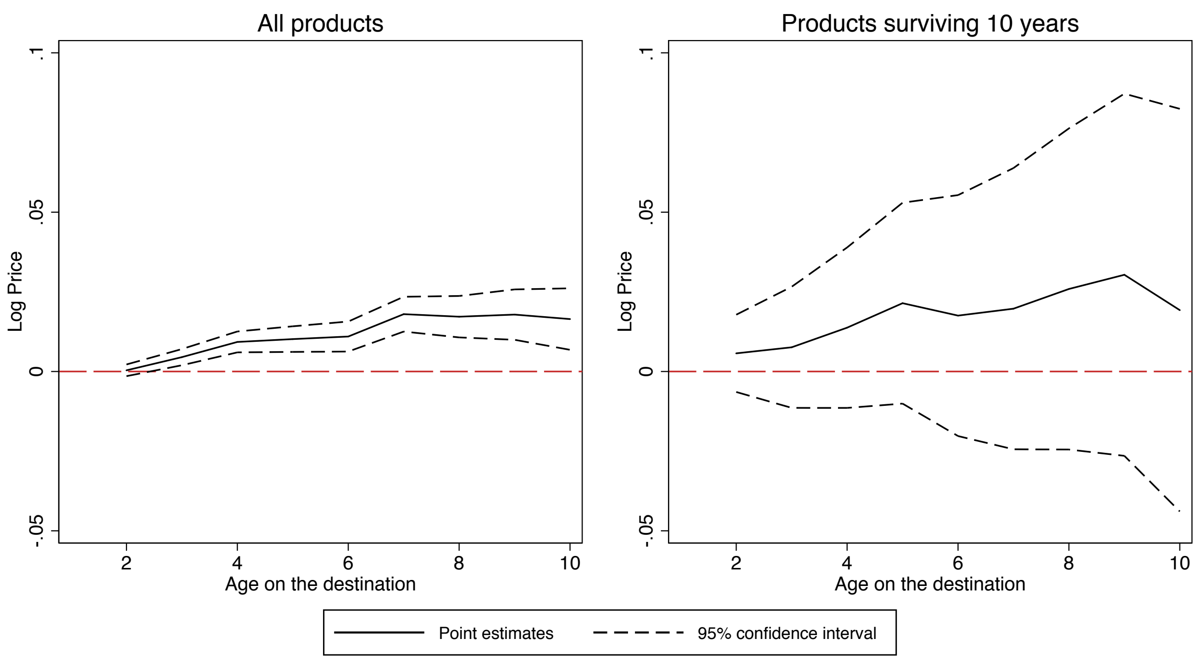


Figure A.5: Prices across export ages, across destinations

Notes: The figure reports the cumulative growth of sales compared to age one, of a firm-product category pair in a destination at different ages. The regression uses logarithm of prices as dependent variable, and includes product category×destination×year and firm×product category fixed effects. The age in a destination is defined as the number of years a firm-product pair has been successively exporting to this country. 95 percent confidence intervals are constructed using standard errors clustered at the firm-product level.

A.2.2 Tables of results

Table A.4: Age regressions (main specification)

	All products			Products surviving 10 years	
	(1) Survival rates	(2) Log sales	(3) Log prices	(4) Log sales	(5) Log prices
Age 2	0.215***	0.550***	0.0207***	0.292***	0.0148
	(0.000675)	(0.00214)	(0.00112)	(0.0162)	(0.0105)
Age 3	0.304***	0.961***	0.0323***	0.528***	0.0304**
	(0.000854)	(0.00317)	(0.00151)	(0.0242)	(0.0112)
Age 4	0.354***	1.240***	0.0470***	0.644***	0.0497***
	(0.00101)	(0.00418)	(0.00189)	(0.0325)	(0.0122)
Age 5	0.380***	1.465***	0.0599***	0.751***	0.0704***
	(0.00118)	(0.00525)	(0.00229)	(0.0410)	(0.0134)
Age 6	0.402***	1.645***	0.0645***	0.795***	0.0795***
	(0.00137)	(0.00652)	(0.00274)	(0.0496)	(0.0143)
Age 7	0.407***	1.808***	0.0771***	0.809***	0.0948***
	(0.00160)	(0.00800)	(0.00330)	(0.0581)	(0.0153)
Age 8	0.419***	1.928***	0.0836***	0.798***	0.114***
	(0.00186)	(0.00973)	(0.00401)	(0.0665)	(0.0163)
Age 9	0.434***	2.051***	0.0855***	0.773***	0.132***
	(0.00215)	(0.0118)	(0.00483)	(0.0752)	(0.0174)
Age 10	0.446***	2.142***	0.0891***	0.637***	0.133***
	(0.00255)	(0.0144)	(0.00574)	(0.0840)	(0.0185)
Constant	0.334***	7.797***	3.799***	9.020***	3.185***
	(0.000290)	(0.00120)	(0.000641)	(0.0431)	(0.0107)
Observations	5311968	5722216	6241358	357751	364700
R^2	0.329	0.439	0.871	0.555	0.918

Notes: Firm x product x destination clustered standard errors between parentheses. Year x product x destinations fixed effects are included in all regressions. * p<0.05, ** p<0.01, *** p<0.001

Table A.5: Age regressions with alternative specifications

	Firm x product f.e.				Firm x product x dest. f.e.	
	All products		Prod. surviving 10 years			
	(1) Log sales	(2) Log prices	(3) Log sales	(4) Log prices	(5) Log sales	(6) Log prices
Age 2	0.244***	0.000369	0.384***	0.00570	0.0230***	-0.00432***
	(0.00231)	(0.000934)	(0.0207)	(0.00619)	(0.00207)	(0.000836)
Age 3	0.493***	0.00450***	0.709***	0.00760	0.0901***	-0.00401***
	(0.00347)	(0.00130)	(0.0330)	(0.00970)	(0.00304)	(0.00114)
Age 4	0.664***	0.00927***	0.912***	0.0137	0.0995***	-0.00421**
	(0.00459)	(0.00167)	(0.0458)	(0.0128)	(0.00398)	(0.00145)
Age 5	0.802***	0.0102***	1.107***	0.0214	0.0903***	-0.00613***
	(0.00577)	(0.00205)	(0.0582)	(0.0161)	(0.00498)	(0.00177)
Age 6	0.911***	0.0110***	1.237***	0.0175	0.0689***	-0.00959***
	(0.00704)	(0.00240)	(0.0706)	(0.0193)	(0.00609)	(0.00211)
Age 7	1.002***	0.0180***	1.339***	0.0197	0.0393***	-0.00617*
	(0.00845)	(0.00279)	(0.0825)	(0.0225)	(0.00731)	(0.00250)
Age 8	1.077***	0.0172***	1.420***	0.0259	0.00299	-0.00958**
	(0.0105)	(0.00332)	(0.0949)	(0.0257)	(0.00883)	(0.00297)
Age 9	1.180***	0.0179***	1.476***	0.0304	0.00423	-0.0122***
	(0.0124)	(0.00403)	(0.107)	(0.0290)	(0.0105)	(0.00349)
Age 10	1.258***	0.0164***	1.412***	0.0193	-0.0287*	-0.0159***
	(0.0147)	(0.00492)	(0.119)	(0.0322)	(0.0125)	(0.00411)
Constant	7.994***	3.812***	8.631***	3.241***	8.184***	3.817***
	(0.00117)	(0.000445)	(0.0603)	(0.0167)	(0.00109)	(0.000412)
Observations	5722216	6241358	357751	364700	5722216	6241358
R^2	0.716	0.960	0.817	0.979	0.873	0.983

Notes: Firm x product x destination clustered standard errors between parentheses. Year x product x destinations and firm x products fixed effects are included in all regressions. * p<0.05, ** p<0.01, *** p<0.001

A.3 Details of the algorithm

I describe in this section of the appendix the MCMC algorithm I implement. I start by describing how the Markov chain is initialized, before describing a given iteration of the chain, involving the update of the unobservables and parameters.

A.3.1 Initial values

I start by describing how the unobservables are obtained, before describing the initial parameters. I start by setting an initial value of 2.2 for σ,[2] that allows me to obtain $\log s_{fdt} + \sigma p_{fdt} = \log n_{fdt} + X_{dt} + \lambda_{ft}$. I can then decompose this term using firm-year and destination-year fixed effect. In order to obtain $\phi_{dt}^{(0)}$, I run the regression $\log p_{fdt} - \frac{\sigma}{\sigma-1}$ on $\lambda_{ft}^{(0)}$. This allows me to obtain $\alpha^{(0)}$, and the residual is regressed on firm-year fixed effects to obtain $\phi_{ft}^{(0)}$. Having in hand initial values for the unobservables, I can use linear regressions to obtain the AR(1) coefficients for the unobservables, and use nonlinear least square to estimate $\underline{n}^{(0)}$, $n_0^{(0)}$, $\eta_1^{(0)}$ and $\eta_2^{(0)}$ after arbitrarily setting $\psi^{(0)} = 0.5$. Finally, I set values for the fixed costs parameters, and the variance parameter of the fixed cost shocks. I arbitrary set $f^{(0)} = fe^{(0)} = s_v^{(0)} = 1\,000$ for the three different groups of countries.

After setting these initial values, I implement 5000 iterations that does not account for the dynamic problem of the firm. Therefore, I sample unobservables and parameters assuming a constant mark-up and only taking advantage of the realized sales and prices. This step allows me to obtain initial conditions for the parameters and unobservables that are closer to their true values, although biased because they do not account for the dynamic problem.

Given this initial set of parameters and unobservables, I can start the iterative procedure described below.

A.3.2 Creation of the grid

In order to solve for the value function as a function of Θ, I need to create a grid describing the state space of the problem. Note that the state space is made of (λ, ϕ, n, X). Consequently, I need a grid that is relatively more precise for values of the unobservables that are more prevalent. Consequently, I create the four-dimensional grid as following

[2] I set $\sigma = 2.2$, which is the elasticity obtained by Broda and Weinstein (2006) for the wine industry. Note that I will keep this value constant through the estimation.

- $\lambda_g \sim N(0, 5\,\mathrm{std}(\lambda_{ft}^{(0)}))$
- $\phi_g \sim N(0, 5\,\mathrm{std}(\phi_{ft}^{(0)}))$
- $X_g \sim N(0, 5\,\mathrm{std}(X_{ft}^{(0)}))$
- $n_g \sim U[\underline{n}^{(0)}\ ;\ 1]$

Note that this grid will be updated every 500 iterations using current unobservables, such that the grid will follow the potential change in the distribution of the unobservables. I will set the size of the grid to be 30 on each dimension, such that the value function will be iterated at 30^4 different grid points.

A.3.3 Iteration

Three different objects will be updated at each iteration of the Markov Chain:

- the history of value function $\left\{V\left(\Theta^{(s-m+1)}\right), ..., V\left(\Theta^{(s)}\right)\right\}$,
- the set of unobservables $\xi_{fdt}^{(s)} = (\lambda_{ft}^{(s)}, \phi_{ft}^{(s)}, X_{dt}^{(s)})$,
- the history of parameter vectors $\left\{\Theta^{(s-m+1)}, ..., \Theta^{(s)}\right\}$.

In the next paragraphs, I describe each of these following steps. I start by describing the step that aims to compute the value functions since they define objects that are used in the other steps. I then turn to the sampling of unobservables, and the sampling of parameters.

Update of the value function The value functions are obtained from the Bellman equation, iterated from the previous iteration of the value functions. However, since the value function depends on the set of parameters Θ, I start by finding the nearest neighbor $\Theta^{(h)}$ of $\Theta^{(s+1)}$ in the history $\left\{\Theta^{(s-m+1)}, ..., \Theta^{(s)}\right\}$. Knowing this nearest neighbor $\Theta^{(h)}$, and its associated value function $V(\xi_g, n_g, \Theta^{(h)})$, I can iterate the value function the following way:

$$V(\xi_g, n_g, \mathcal{I}, \Theta^{(s+1)}) = s_v \log \Bigg[\exp\left(\frac{1}{s_v} \max_{n' \in n_g} \left\{ E_\varepsilon \pi(\xi_g, n_g, n', \Theta^{(s+1)}) - FC(\mathcal{I}) + EV(\xi_g, n', 1) \right\} \right) + \exp\left(\frac{1}{s_v} EV(\xi_g, n_0, 0) \right) \Bigg] \tag{A.1}$$

$$\text{with} \qquad EV(\xi_g, n, I) = \frac{\sum_{\xi \in \xi_g} V(\xi, n, I, \Theta^{(h)}) \; P_\xi(\xi \,|\, \xi_g)}{\sum_{\xi \in \xi_g} P_\xi(\xi \,|\, \xi_g)},$$

$P_\xi(.|.)$ being the transition probability of the unobservables at the current parameters. In practice, I can iterate several times the Bellman equation, in order to reduce the error coming from the choice of a nearest neighbor instead of the exact parameter. In this case, I iterate not using the m-th value function anymore, but the current value function and its grid.

In addition to updating the value function, I will define two objects based on the recently updated value functions, that will be used in the sampling of parameters and unobservables. First, I will save the optimal future share of consumer chosen by the firm. This object, evaluated on the grid, will be defined as

$$n_g^* \equiv n'^*(\xi_g, n_g) = \text{argmax}\Big\{ E_\varepsilon \pi(\xi_g, n_g, n') + EV(\xi_g, n', 1) \Big\}.$$

Second, I will create the difference in expected value functions, $DEV()$, that will be defined as

$$DEV(\xi_g, n_g) = EV(\xi_g, n_g^*, 1) - EV(\xi_g, n_0, 0).$$

This object will be convenient when computing the difference in value functions for each firm.

These new value functions are stored in the history of the value functions for later use in the algorithm. The functions $n^*()$ and $DEV()$ will be used in the next iteration to sample the unobservables.

Sampling of unobservables The marginal density of the unobservables (λ, ϕ or X) is made of three parts:

- the unconditional distribution of the unobservables,
- the entry condition,

- the demand and supply equations.

As an illustration, when looking at a given λ_{ft}, its density, conditional to all the other parameters and unobservables, is

$$\begin{aligned}\lambda_{ft}|... \propto \exp\left(-\frac{1}{2\sigma_\lambda^2}\left(\lambda_{ft}-\rho_\lambda\lambda_{ft-1}\right)^2-\frac{1}{2\sigma_\lambda^2}\left(\lambda_{ft+1}-\rho_\lambda\lambda_{ft}\right)^2\right)\\ \times\prod_{d=1}^{D}\left\{\exp(U'_{fdt}\Sigma^{-1}U_{fdt})^{\mathcal{I}_{fdt}}\left[1+\exp\left(\frac{-DV(\xi_{fdt},n_{fdt})+FC(\mathcal{I}_{fdt-1})}{\sigma_\nu}\right)\right]^{-\mathcal{I}_{fdt}}\right.\\ \left.\left[1+\exp\left(\frac{DV(\xi_{fdt},n_{fdt})-FC(\mathcal{I}_{fdt-1})}{\sigma_\nu}\right)\right]^{\mathcal{I}_{fdt}-1}\right\}\end{aligned} \tag{A.2}$$

with

$$U_{fdt}=\begin{pmatrix}\log s_{fdt}-\log n_{fdt}-\lambda_{ft}-X_{dt}+\sigma\log p_{fdt}\\ \log p_{fdt}+\phi_{ft}-\alpha\lambda_{ft}-\log\mu(\xi_{fdt},n_{fdt})\end{pmatrix}.$$

I use a Metropolis-Hastings algorithm to sample from this distribution. For each period t, from t=0 to t=T, I draw a set of unobservables λ^*_{ft} from their hierarchical distributions (first line of the formula (A.2)). Then these new draws are accepted, firm by firm, based on the evaluation of the multivariate normal and exporting probabilities (second and third line from (A.2)).

The complexity comes from evaluating the functions $DV()$ and $\mu()$ at the proposed unobservables ξ^*. In order to do so, I follow these steps:

- Obtain the targeted n^* for each observation, from interpolation of $n^*()$: $n^*_{fdt}=n^*(\xi_{fdt},n_{fdt})$.
- Compute the contemporaneous profit analytically: $\pi_{fdt}=\pi(\xi_{fdt},n_{fdt},n^*_{fdt})$.
- Evaluate the difference in expected value functions from interpolation $DEV_{fdt}=DEV(\xi_{fdt},n_{fdt})$ to obtain $DV_{fdt}=\pi_{fdt}+\beta DEV_{fdt}-FC(\mathcal{I}_{fdt})$.
- From the first order condition, I obtain a analytic formula for μ: $\mu_{fdt}=\frac{\partial\pi(\xi_{fdt},n_{fdt},s(n^*_{fdt}))}{\partial s(n^*_{fdt})}$.

With the values in hand, it is then straightforward to compare firm by firm the conditional densities using λ^* and $\lambda^{(s)}_{ft}$. Once this procedure has been applied for all periods from t=0 to t=T, the same sampling is applied to ϕ_{ft} and X_{dt}, allowing us to obtain a new set of unobservables $\xi^{(s+1)}_{fdt}$.

Sampling of parameters The sampling of parameters is somewhat similar to the unobservables. However, the main difference is that the functions $DEV()$ and $\mu()$ need to be reevaluated for a new Θ, rather than for new unobservables. Consequently, for all the parameters, a Metropolis-Hastings sampler needs to be used. As a second consequence, it is necessary to iterate the value functions for this new parameter Θ in a similar manner than the update of the value functions.

Formally, the sampling of a given block of parameter Θ takes the following steps:

- A new parameter Θ^* is drawn using proposal functions.
- The nearest neighbor of Θ^* is found in the history $\left\{\Theta^{(s-m+1)}, ..., \Theta^{(s)}\right\}$.
- The value function $V(\xi_g, n_g, I, \Theta^*)$ is obtained from equation (A.1) and the functions $DEV(\xi_g, n_g)$ and $\mu(\xi_g, n_g)$ are obtained.
- I obtain by interpolation DV_{fdt} and μ_{fdt} as in the step updating the unobservables, allowing me to compute the likelihood function.
- $\Theta^{(s+1)}$ is set to be Θ^* with probability $\max\left\{1, \frac{\prod_t \prod_d \prod_f L_{fdt}(D, \xi_{fdt}^{(s+1)}; \Theta^*)}{\prod_t \prod_d \prod_f L_{fdt}(D, \xi_{fdt}^{(s+1)}; \Theta^{(s)})}\right\}$.

In order to make the update of the parameters more tractable, I divide my set of parameters in blocks, as it is usually done when the set of parameters is large. The blocks of parameters and their proposal functions are the following:

- α, and γ_d using a random walk proposal function that targets an acceptance rate of 0.25,
- η_1, η_2, n_0, $\underline{n}$ and ψ using a random walk proposal function that targets an acceptance rate of 0.25,
- Σ using a Wishart distribution from the previous Σ parameters that targets an acceptance rate of 0.3,
- ρ_ϕ, σ_ϕ, μ_ϕ using a random walk proposal function that targets an acceptance rate of 0.25. A similar step is implemented for X and λ,
- f and fe, using a random walk proposal function that targets an acceptance rate of 0.2,
- s_ν using a random walk proposal function that targets an acceptance rate of 0.4.

A.3.4 Test on simulated data

To test my empirical procedure, I simulate a set of data following the data generating process assumed in the model. Then, I implement my estimation procedure to test the validity of the estimation. However, because of the complexity of the estimation, I cannot perform a full Monte Carlo study of the estimation method. Therefore, I cannot test if my estimator consistently recovers the true value of the parameters, but instead whether the true value of the parameters belongs to the confidence interval obtained from the estimation. I simulate data for 200 firms, 15 years and 15 destinations and I run 80 000 iterations of my algorithm, discarding the first 40 000, as I do in the estimation procedure. I report in figures A.6 and A.7 the Markov chains and the posterior distributions for the fixed costs of exporting, as well as the true value of the parameters displayed by the red lines. As displayed on these figures, the estimation provides confidence intervals that are consistent with the true value of the parameters.

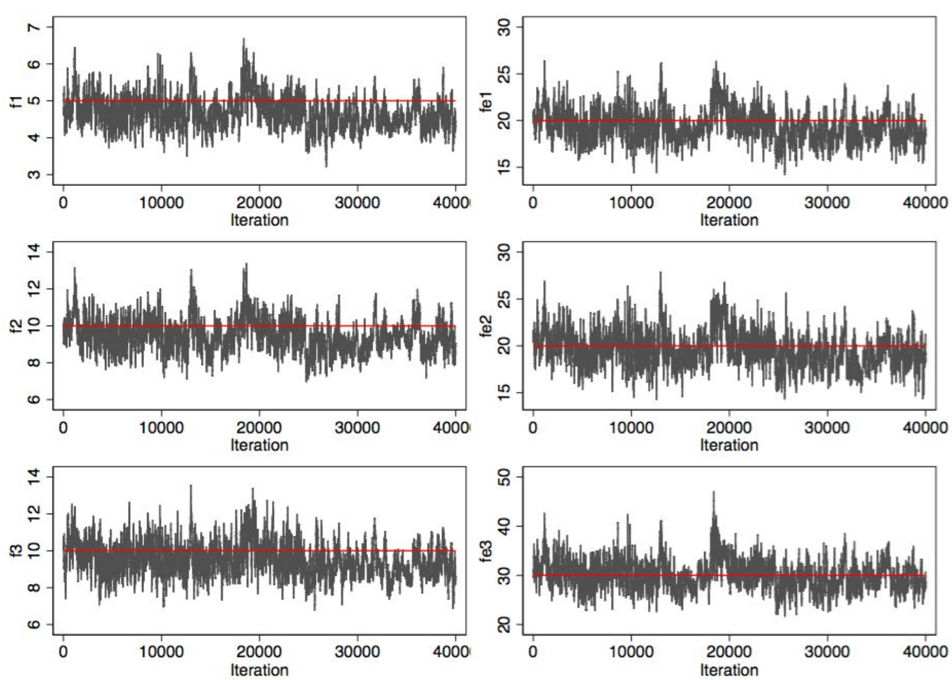


FIGURE A.6: Markov Chains for fixed costs on simulated data.

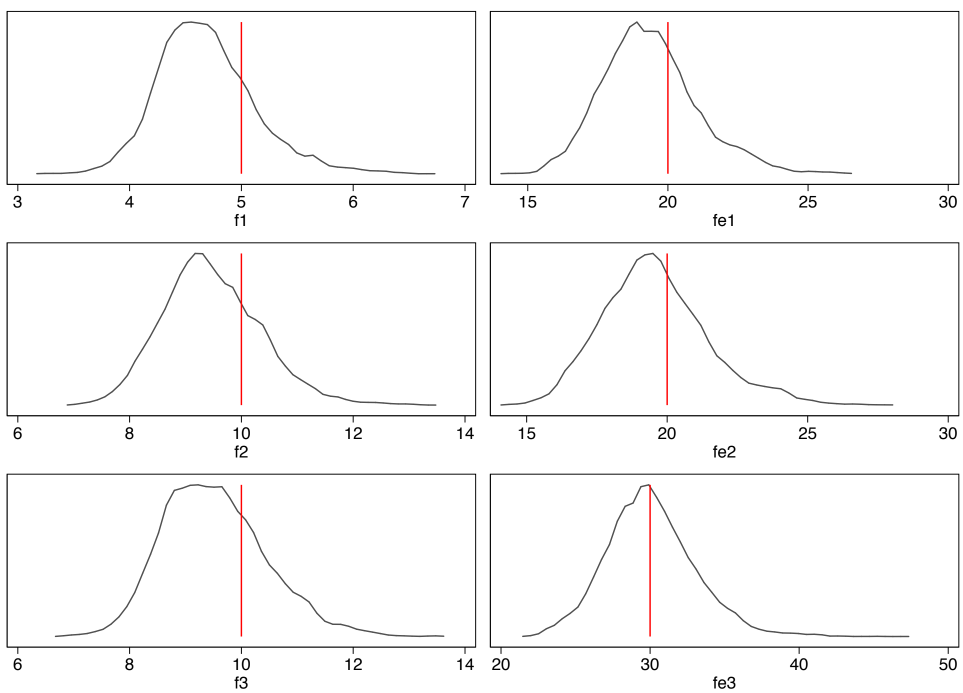


Figure A.7: Posterior distributions for fixed costs on simulated data.

A.4 Additional figures

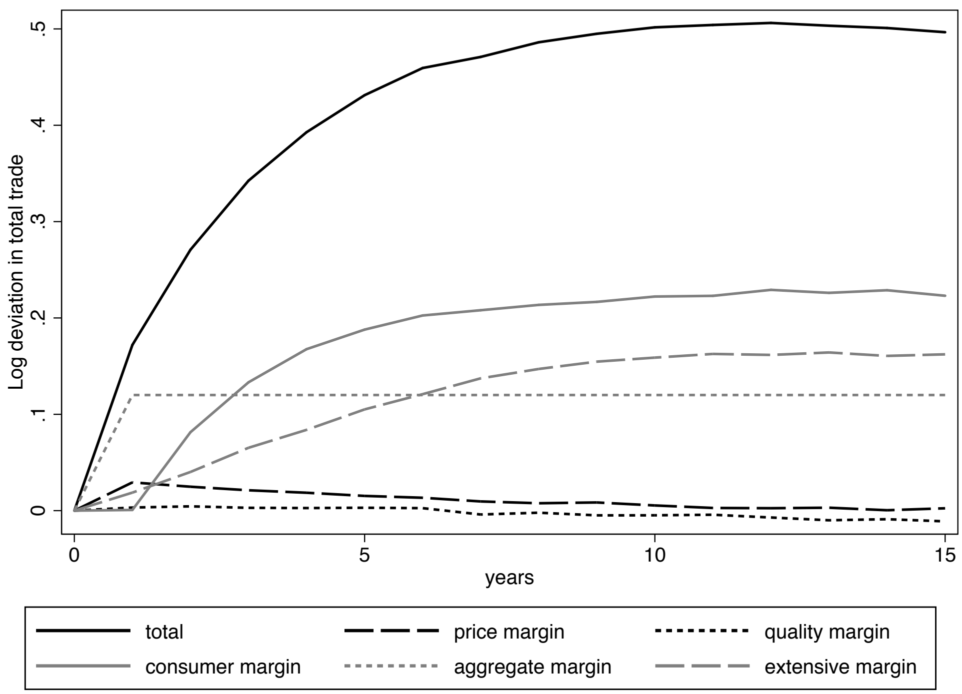


Figure A.8: Effect of permanent 10 points tariffs decrease (All margins).

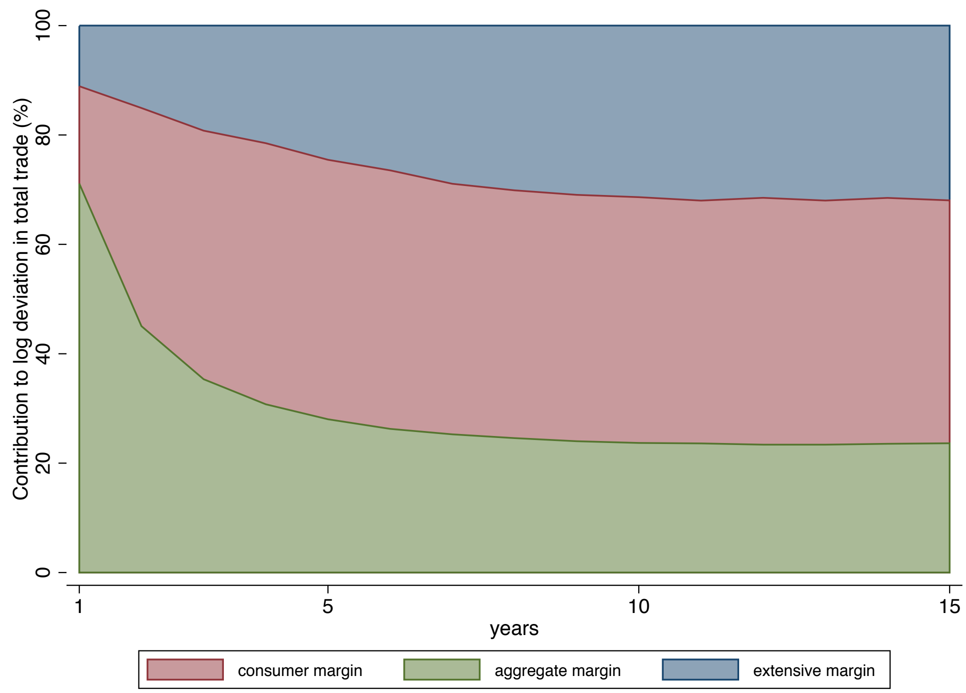


Figure A.9: Contribution of different margins to trade expansion.

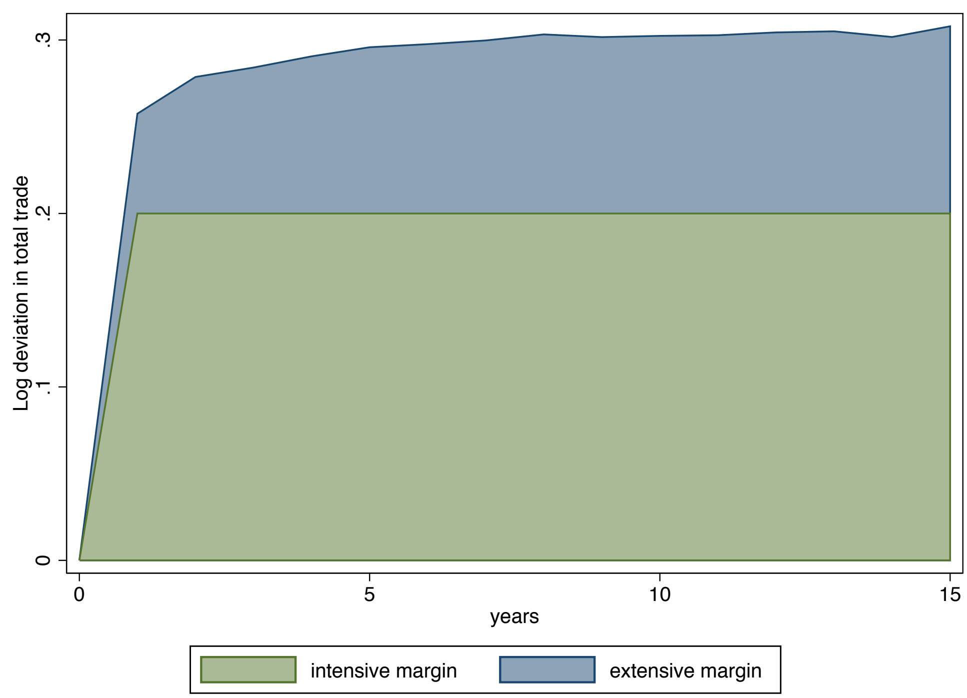


Figure A.10: Effect of permanent 10 points tariffs decrease (Restricted model).

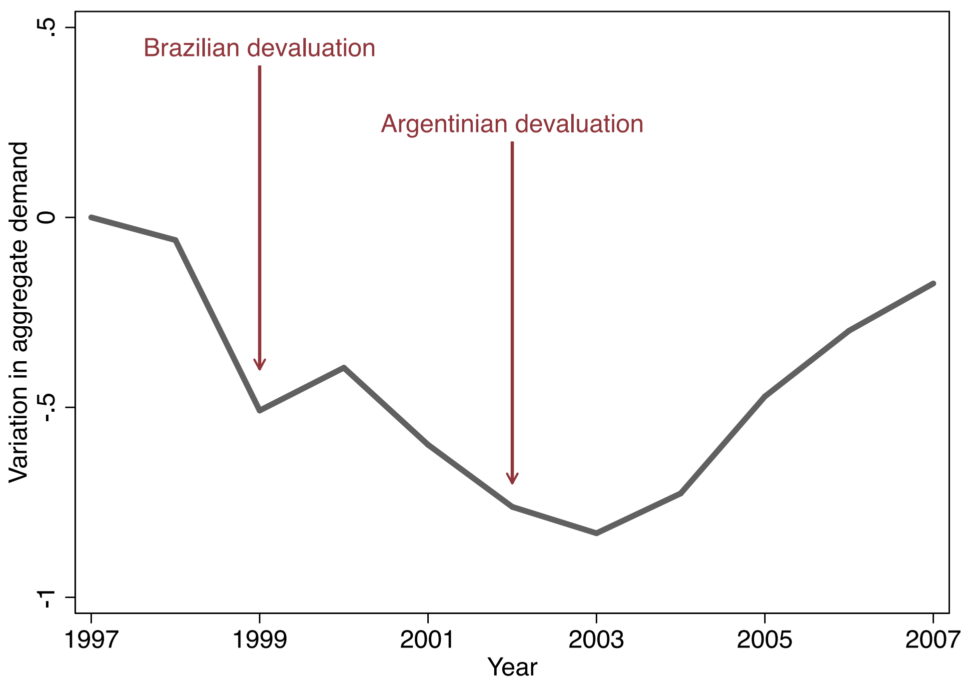


FIGURE A.11: Computed variations in aggregate demand for French wine from Brazil.

Appendix B

Appendix for Chapter 2

B.1 A Simple Model of Endogenous Quality with Imported Inputs

In this section, we develop a partial equilibrium model with heterogeneous firms, endogenous product quality, and imported inputs. The model builds upon the first variant of Kugler and Verhoogen (2012)'s model: quality impacts variable production costs, not fixed costs. We extend the original model by assuming that production is obtained by combining a set of imported inputs rather than just a single input. The main purpose of this simple model is to ground theoretically the validity of our instrument for prices. The model formalizes the relationship between the RER's faced by a firm on its imports and its export price and hence motivates our first stage. As to the exogeneity of the instrument, the model predicts that importing shares are endogenous to quality and thus suggests that importing shares should be set constant in the instrument, which is what we do in the estimation. Moreover, the model delivers a mechanism through which quality could be endogenous to RER's on imports. This potential endogeneity of the instrument can be neutralized by controlling for a sufficient statistic also provided by the model.

In addition to its predictions on the validity of the instrument, the model delivers implications on the quality response to low-cost competition, the model predicts that firms in the lower end of the quality ladder should upgrade their quality to escape competition from new entrants.

B.1.1 Technology

As in the model of demand developed in section 2.2, the unit of analysis is a variety of a differentiated final good [1]. A variety is produced by combining inputs from different sources. For each input, a firm must decide the quality and the number of physical units involved in the production of a variety. These decisions impact the volume and the quality of the output. This production process is thus described by two functions: one for physical production, another one for the production of quality. The physical production function is:

$$x_{v,t} = \varphi_{v,t}^{a} \left(\sum_{s \in \mathcal{S}_v} \gamma_{v,s} . [z_{s,v,t}]^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}}, \tag{B.1}$$

with $x_{v,t}$ the physical output and $z_{s,v,t}$ the quantity of input from source s involved in the production of variety v. Remark that in order to make the notation simpler, in this appendix we rely on a single index v to identify a variety, instead of the triplet fpd. κ is the elasticity of substitution across inputs. $\gamma_{v,s}$ is the weight of input from s in the production of v ($\sum_{s \in \mathcal{S}_v} \gamma_{v,s} = 1$). $\varphi_{v,t}$ is what Kugler and Verhoogen (2012) refer to as "capability". As it appears in (B.1), $\varphi_{v,t}$ is of the same nature as total factor productivity: it shifts up output conditional on inputs. However, unlike physical productivity, and as will be formalized below, capability also plays a role in the production of quality. Parameter a is simply the capability-elasticity of physical output. We assume $a > 0$.

$\mathcal{S}_v$ is the set of source countries of a firm. We take $\mathcal{S}_v$ as fixed and given. Our sense is that making $\mathcal{S}_v$ endogenous and varying (by assuming fixed export costs for instance) would not change the main qualitative insights of the model.

Inputs are vertically differentiated. Input quality determines output quality through following function:

$$q_{v,t} = \left[\frac{1}{2} \left(\varphi_{v,t}^{b} \right)^{\theta} + \frac{1}{2} \left(\min \left\{ q_{I,s,v,t} \right\}_{s \in \mathcal{S}_v} \right)^{\theta} \right]^{\frac{1}{\theta}}, \tag{B.2}$$

with $q_{v,t}$ output quality and $q_{I,s,v,t}$ input s quality. The production of quality is CES in capability and in the quality of imported inputs. The innovation with respect to Kugler and Verhoogen (2012) is that a firm must decide on the quality not of a single input but of many inputs. Here we assume

[1] In this model, a firm is a collection of independent production lines, each line producing a variety.

that different input qualities combine through a Leontief production function. This specification is convenient as it boils down the quality choice of a firm to picking a unique quality level which is invariant throughout the different inputs it imports. A more flexible CES form would leave our main qualitative results unaltered.[2]

We assume $\theta < 0$ so that input quality and capability are complementary. This means that the quality upgrading obtained from a marginal increase in the quality of inputs is larger for high capability firms/varieties. This structure leads higher capability firms to produce higher quality goods. Parameter b simply drives the elasticity of output quality to capability: a higher b gives a larger incentive to higher φ firms to produce high quality goods. We assume $b > 0$.

The last technology assumption is related to the price of inputs. In each country, the input is produced from labor under perfect competition and constant returns to scale. Unit labor requirements are a power function of input quality. As a result, the price of input from source s with quality q_I is:

$$p^*_{I,s,t}(q_I) = w_{s,t} q_I^{\beta_s} \tag{B.3}$$

$p^*_{I,s,t}(q_I)$ is the FOB (Free on board) price of input with quality q_I labelled in s's currency. $w_{s,t}$ is the unit wage rate in s. β_s is the elasticity of input price to quality in source s. One should think of β_s as the relative price of high to low quality in country s. As evidenced by Schott (2004), rich countries have a comparative advantage in the production of high quality goods. In terms of the model, it means that β_s is larger for poor countries. The key implication of specification (B.3) is that the optimal spatial allocation of a firm's imports depends on a firm's quality: high quality firms import high quality inputs from low β (rich) countries.

Imports of inputs involves iceberg costs. The CIF cost of an input s with quality q_I, labelled in home currency (one should think of home as France, consistently with the empirical application) is:

$$p_{I,s,t}(q_I) = e_{s,t} \tau_{s,t} p^*_{I,s,t}(q_I)$$

with $e_{s,t}$ the direct nominal exchange rate between home and s and $\tau_{s,t}$ the iceberg trade cost

[2] In the next subsection, we discuss the fact that allowing for more substitutability across qualities plays in favor of the validity of our instrument. In that sense, the Leontief specification is conservative.

between home and s ($\tau \geq 1$).

The next subsection solves the optimal price, import shares and quality of the firm and draws the implications for the validity of our instrument for export prices.

B.1.2 Optimal Prices, Quality and Import Shares and the Role of RER's

In this subsection, we derive the expression of firms optimal pricing, quality and import decisions and we discuss the implications for the validity of our instrument $\overline{RER}_{v,t}$.

The rank condition: export prices depend on import-side RER's A variety v faces demand (2.2). We assume that competition is monopolistic so that firms charge a constant mark-up over their marginal cost:

$$p_{v,t} = \frac{\sigma}{\sigma - 1} mc_{v,t}$$

We obtain the expression of the marginal cost of a firm (conditional on output quality) as follows. First, we use the fact that, due to the Leontief assumption, a firm imports a single input quality. So one can invert (B.2) to get input quality as a function of output quality. By plugging this relationship into (B.3), we get input prices as a function of output quality. Finally, minimizing the production cost of a firm subject to (B.1) over input quantities $z_{v,s,t}$ gives

$$mc_{v,t}(q) = \varphi_{v,t}^{-a} \left(\sum_{\mathcal{S}_v} \gamma_{v,s}^{\kappa} \left[\tau_{s,t} e_{s,t} w_{s,t} \left(2q^{\theta} - \left(\varphi_v^b \right)^{\theta} \right)^{\frac{\beta_s}{\theta}} \right]^{1-\kappa} \right)^{\frac{1}{1-\kappa}}. \quad \text{(B.4)}$$

The marginal cost of a firm is simply a CES index of CIF import prices. Equation (B.4) formalizes the idea that marginal costs, and hence output prices, are endogenous to output quality. This explains the need to instrument prices when estimating demand functions. Thankfully, equation (B.4) also provides us with a candidate instrument for prices: RER's on imports, which in terms of the model is equal to $e_{s,t} w_{s,t}$. Equation (B.4) says that $e_{s,t} w_{s,t}$ affects output prices and thus verifies the rank condition. Yet, to be a valid instrument, the average RER on imports should also be orthogonal to quality q. We verify this theoretically in the next paragraph by analyzing optimal quality.

Exogeneity Condition: Do Import Shares depend on RER's? Our instrument is an import weighted average RER at the firm level. In the estimation, we set import weights constant as there is a concern that they are endogenous to a firm's quality. The present model formalizes this intuition and hence justifies the use of constant weights. The expression of optimal import weights, conditioning on quality is

$$\omega_{s,v,t}(q) = \frac{\gamma_{v,s}^{\kappa}\left(e_{s,t}\tau_{s,t}w_s q_I^{\beta_s}\right)^{1-\kappa}}{\sum_{s'\in\mathcal{S}_v}\gamma_{v,s'}^{\kappa}\left(e_{s',t}\tau_{s',t}w_{s',t}q_I^{\beta_s'}\right)^{1-\kappa}},$$

where $\omega_{s,v,t}$ is the share of source s in total imports by variety v.

This weight is a function of quality. To better understand the way a firm sets its weights, let us write the elasticity of a weight to input quality:

$$\frac{\partial \log \omega_{s,v,t}(q)}{\partial \log q_I} = -(\kappa-1)\left(\beta_s - \sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)\right). \tag{B.5}$$

Expression (B.5) has an intuitive interpretation. When a firm upgrades its quality, it reallocates its imports towards sources in which the relative cost of quality, β_s, is low, relative to the average cost in its source portfolio, $\sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)$. It follows that high quality firms import from countries with low β (i.e. developed countries, according to (Schott, 2004)). If the RER of a source s is correlated to its β_s (i.e if high wage countries have a comparative advantage in high quality inputs), then the average RER of a firm is correlated to its quality, through its import shares: high quality firms import from developed countries, which have strong currencies. It is therefore necessary to fix import weights, as we do in the estimation, to guarantee the exogeneity of the instrument.

Exogeneity Condition (continued): Is output quality endogenous to RER's? The optimal quality of a firm maximizes profit function:

$$\pi_{v,t}(q) = \frac{1}{\sigma}p_{v,t}^{*}(q)^{1-\sigma}q^{\sigma-1}P_{m,t}^{\sigma-1}E_{m,t} \tag{B.6}$$

with index m standing for "market" and substituting for product-destination index p, d used in the main text, as a way to simplify notations.

We assume that exporting involves iceberg costs, so the CIF price labelled in m's currency, $p^*_{v,t}(q)$, verifies

$$p^*_{v,t}(q) = e^{-1}_{m,t}\tau_{m,t}p_{v,t}(q)$$

It follows that the first order condition on quality is:

$$\underbrace{(\sigma-1)}_{\substack{\text{Price elasticity}\\ \text{of sales}}} \underbrace{\left[\frac{\sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)}{1-\left(\frac{\varphi^b_{v,t}}{2q}\right)^{\theta}}\right]}_{\substack{\text{Quality elasticity}\\ \text{of marg. costs.}}} = \underbrace{\sigma-1}_{\substack{\text{Quality elasticity of}\\ \text{sales}}} \tag{B.7}$$

To choose their optimal quality, firms operate a quality-cost trade-off. From equation (B.7) it appears that the optimum is reached when a firm equalizes the quality-elasticity of its demand shifter to the quality-elasticity of its production costs. Equation (B.7) implicitly defines optimal quality. It appears that optimal quality is a function of importing shares $\omega_{s,v,t}$. The rationale for that prediction hinges on the leontief assumption on the quality of the basket of inputs. When a firm decides to upgrade its quality, it must increase the quality imported from its whole input basket. By how much the cost of its input basket goes up as a consequence depends on the import weighted average elasticity of input prices to quality: $\bar{\beta}_{v,t}(q) = \sum_{\mathcal{S}_v}\beta_s\omega_{s,v,t}(q)$.

Importing shares are also a function of RER's. This is very intuitive: firms minimize their production cost by importing from weak currency sources. Consequently, when a RER shock occurs, firms adjust their importing share which as a result impacts their perceived relative cost of quality $\bar{\beta}_{v,t}(q)$ and eventually leads the firm to adjust its quality. To make this mechanism more practical, consider the example of a firm importing from a developing country with a high β, say China, and from a developed country with a low β, say the USA. If Yuan appreciates, then the firm reallocates its imports towards the USA, this decreases the quality-elasticity of its production costs and so the firm upgrades its quality.

The crucial implication of this discussion is that quality is potentially endogenous to RER shocks.[3] If this questions the validity of our instrument, note that the sign of the bias which would

[3] How does this result depend on the Leontief assumption in the production of quality? Intuitively, it the firm could combine the quality of its inputs through a CES function with strictly positive elasticity of substitution, it

result from the relationship between RER and quality is unclear. To see this, let us consider previous example again. Here, the firm faces a positive cost shock (Yuan appreciates) and simultaneously upgrades its quality. This suggests that the price elasticity obtained through our IV estimation is biased upward. Now take a symmetric situation where the dollar appreciates instead of the Yuan. Then the firm reallocates its imports towards China and downgrades its quality. This case would rather suggest a negatively biased price elasticity estimate.

Equation (B.7) also predicts that conditional on $\bar{\beta}_{v,t}$, quality is exogenous to RER's. In terms of our estimation, this means that our instrument is valid once $\bar{\beta}_{v,t}$ is controlled for in the estimation. As we think of β_s as a measure of development of a country, a natural proxy for $\bar{\beta}_{v,t}$ is the import weighted average income per capita of a firm. In section 2.3, we show that our price elasticity estimates are robust to whether we control on not for $\bar{\beta}_{v,t}$. This is consistent with the idea that the sign of the bias, if any, is not clear theoretically.

B.2 Low-Quality Competition and Quality Upgrading

In section 2.5, we report evidence that firms upgrade the quality of their products as a reaction to low-cost competition. The present section proposes a model rationalizing this behavior.

The supply side of the model is the same as the endogenous quality model developed in appendix B.1. This involves in particular that marginal production costs are increasing with product quality. On the demand side, we consider a slightly modified version of demand system (2.1). Instead of assuming that the representative consumer has simple CES preferences over the different varieties of a CN8 product, we suppose that her preferences are nested at the quality level:

$$U_{dt} = U\left(C_{1gt}, .., C_{Gdt}\right),$$
$$\begin{cases} C_{gdt} = \left[\int \left(q.X_{gdt}(q)\right)^{\frac{\rho-1}{\rho}} dq\right]^{\frac{\rho}{\rho-1}} \\ X_{gdt}(q) = \left[\sum_{f\in\Omega_{gdt}(q)} x_{fgdt}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \end{cases} \quad \forall\, g = 1..G, \tag{B.8}$$

could concentrate its imports of quality from a country with a low β, and import large physical amounts of low quality inputs from the rest of the world. Therefore, the cost of upgrading its quality would be driven by the β of the source from which it imports quality, and not from its all input portfolio. It follows that the reallocation of its physical imports induced by a RER shock would have little impact on its choice of quality. The leontief specification therefore is the most challenging for our instrument as it is the case where quality is the most endogenous to RER. In that sense it is a conservative assumption.

with $X_{gdt}(q)$ the aggregate consumption of product g varieties with quality q, $\Omega_{gdt}(q)$ the set of firms serving product g with quality q and ρ the elasticity of substitution between different varieties with same quality. We assume $\rho > \sigma$ to capture the intuitive feature that varieties are closer substitutes within quality nests than between. This demand system delivers following demand function at the variety level:

$$r_{vt}(q) = {p^*_{vt}}^{1-\sigma} q^{\rho-1} \tilde{P}_{mt}(q)^{\sigma-\rho} P_{mt}^{\rho-1} E_{mt}, \tag{B.9}$$

with index v (for "variety") standing for a firm-product-destination combination fpd, m (for "market") standing for a product-destination combination, $\tilde{P}_{mt}(q)$ the price index specific to quality level q and P_{mt} the aggregate price index.[4].

As a firm upgrades the quality of its products, its demand function gets shifted for two reasons. First, the good produced by the firm is now more appealing so that consumers are willing to buy more of it, all things equal. Second, as the firm climbs up the quality ladder, it changes quality nests and so faces new direct competitors. If these new competitors charge higher prices or are less numerous, i.e if the quality-specific price index $\tilde{P}_{mt}(q)$ is increasing with q, the firm will enjoy a larger residual demand.[5]

Naturally, firms take into account this competition effect when choosing the quality of their products. This can be seen through the expression of the first order condition on quality:

$$(\sigma - 1) \underbrace{\left[\frac{\sum_{\mathcal{S}_v} \beta_s \omega_{s,v,t}(q)}{1 - \left(\frac{\varphi^b_{v,t}}{2q}\right)^{\theta}} \right]}_{\substack{\text{Quality-Elasticity} \\ \text{of marg. costs.}}} = \underbrace{(\rho - 1) + \frac{\partial \log \tilde{P}_{m,t}(q)}{\partial \log q}}_{\substack{\text{Quality-Elasticity of} \\ \text{the demand Shifter}}}. \tag{B.10}$$

[4]Quality-specific and aggregate price indices verify:

$$\tilde{P}_{mt}(q) = \left(\sum_{f \in \Omega_{mt}(q)} {p^*_{vt}}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

$$P_{mt} = \left[\int \left(\frac{\tilde{P}_{mt}(q)}{q} \right)^{1-\rho} dq \right]^{\frac{1}{1-\rho}}$$

[5]Notice that this second effect vanishes as ρ converges to σ since in that case the intensity of competition faced by a firm is independent of its position on the quality ladder.

Upgrading quality decreases profits because it increases marginal production costs (left hand side of equation (B.10)). At the same time, increasing quality shifts the demand faced by a firm for the reasons explained above which translates into higher profits (right hand side of equation (B.10)). The optimal quality of a firm equalizes the marginal profit loss to the marginal profit gain. Interestingly, first order condition (B.10) implicitly defines optimal quality as an increasing function of $\frac{\partial \log \tilde{P}_{m,t}(q)}{\partial \log q}$, the partial derivative of the price index with respect to quality.

What implications does it have on firms' reaction to the entry of low-cost firms? Because these firms presumably produce low quality goods, their entry intensifies competition at the bottom of the quality ladder. Formally, $\frac{\partial \log \tilde{P}_{m,t}(q)}{\partial \log q}$ increases. From first order condition (B.10), we get the data-consistent prediction that incumbent firms adjust by upgrading their quality. The model therefore delivers an escape competition motive for firms' quality response to low-cost competition.

B.3 Data Trimming

Data on quantities are known to be subject to measurement errors, which could lead to spurious relationships between quantities and prices (computed by dividing values with quantities). Because variations across prices are less subject to idiosyncratic variations than values, we clean the data, based on their computed prices, following three dimensions.

- Observations are dropped for prices for which variations across times differ from a factor two or more. Formally, observations are dropped if $\frac{p_{fpdt}}{p_{fpdt-1}} > 2$ or $\frac{p_{fpdt}}{p_{fpdt-1}} < \frac{1}{2}$
- Observations are dropped for prices which differ from a factor two or more from the mean across all destinations. Formally, observations are dropped if $\frac{p_{fpdt}}{p_{fp\bullet t}} > 2$ or $\frac{p_{fpdt}}{p_{fp\bullet t}} < \frac{1}{2}$
- Extreme quantiles of the price distributions are censored: for each market (product $\times$ destination $\times$ year), observations below the 1st percentile, and beyond the 99th percentile are dropped.

Finally, for several observations, quantities are displayed in different units than weight. We convert these units in weight by regressing weights on units at the product$\times$year level. Therefore, we are able to back-up the weight equivalent of these units.

B.4 Descriptive Statistics

Table B.1: Descriptive Statistics for all exporters

		p5	**p25**	**p50**	**p75**	**p95**	**Mean**
# **Products**	*by firm-year pair*	1	1	2	5	21	5.7
# **Destinations**	*by firm-year pair*	1	1	2	4	18	4.5
# **Products**	*by firm-country-year comb.*	1	1	1	2	9	2.9
# **Destinations**	*by firm-product-year comb.*	1	1	1	2	8	2.3
# **Years**	*by flow*	1	1	3	6	13	4.3
# **Flows**	*by market*	1	1	2	4	20	5.7

Notes: A 'flow' is a combination of a firm, a product and a destination. A 'market' is a combination of a product, a destination and a year.

B.5 Correlation of import shares

Table B.2: Persistence of Import Shares over Time

Year t	**Correlation Import Shares** $(\omega_{fs1995}, \omega_{fst})$	**N**
1995	1.000	185,277
1996	0.850	120,282
1997	0.795	105,671
1998	0.761	97,060
1999	0.717	89,930
2000	0.691	83,164
2001	0.676	75,518
2002	0.658	69,734
2003	0.643	64,937
2004	0.630	61,449
2005	0.611	57,496
2006	0.604	54,418
2007	0.589	51,651
2008	0.585	49,079
2009	0.577	45,568
2010	0.563	44,044

Notes: This table reports the auto-correlation of firm-country import shares over time All correlations are significant at 1%

B.6 Robustness checks

Table B.3: Robustness checks

	Base	No hedging		Long diff.		No crisis
	(1)	(2)	(3)	(4)	(5)	(6)
First stage:						
$\bar{RER}_{ft}$	0.092***	0.083***	0.089***	0.071***	0.099***	0.083***
	(0.005)	(0.012)	(0.008)	(0.007)	(0.008)	(0.006)
$\bar{gdpc}^{\mathbf{exp}}_{ft}$	0.007***	0.009***	0.010***	0.004***	0.008***	0.006***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$\bar{gpdc}^{\mathbf{imp}}_{ft}$	0.012***	0.006***	0.008***	0.008***	0.012***	0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Second Stage:						
Log(Price)	-1.35	-1.30	-1.67	-2.38	-1.93	-0.89
	(0.18)	(0.51)	(0.33)	(0.31)	(0.26)	(0.22)

Notes: Specification (1) is the baseline from column (3), table 2.4. Columns (2) and (3) dropped importers who export to the same country: specification (2) does it for a given year, specification (3) for any year in the sample. Specifications (4) and (5) respectively use 3 and 5 years differences instead of flow fixed effects. Finally, specification (6) drops years posteriors to 2007 to avoid the role played by the trade collapse phenomenon. All specifications use the gdp per capita controls in the second stage, even though the results are not displayed.

B.7 Additionnal consistency tests

B.7.1 Correlation with firms' characteristics

Table B.4: Correlation with firms' characteristics

	Log wages		
Estimated quality λ_{fdt}	0.0106***		0.0110***
	(0.0018)		(0.0020)
Log employment		-0.00257	-0.00513
		(0.0049)	(0.0051)
N	3 605 570	3 738 853	3 605 570

Notes: Firm-level clustered standard errors in parentheses. *** $p < 0.01$.

B.7.2 Quality ladder lengths

Table B.5: Revealed Quality Ladders

	Quality Ladder: $q^{95}_{pdt}(\lambda) - q^{5}_{pdt}(\lambda)$
Sutton	1.314***
	(0.097)
N	2,059,636
R-squared	0.001

Notes: Quality ladder is the difference between the 95th percentile and 5th percentile of quality for each destination-product-year triplet. Robust s.e. in parentheses. *** $p < 0.01$.

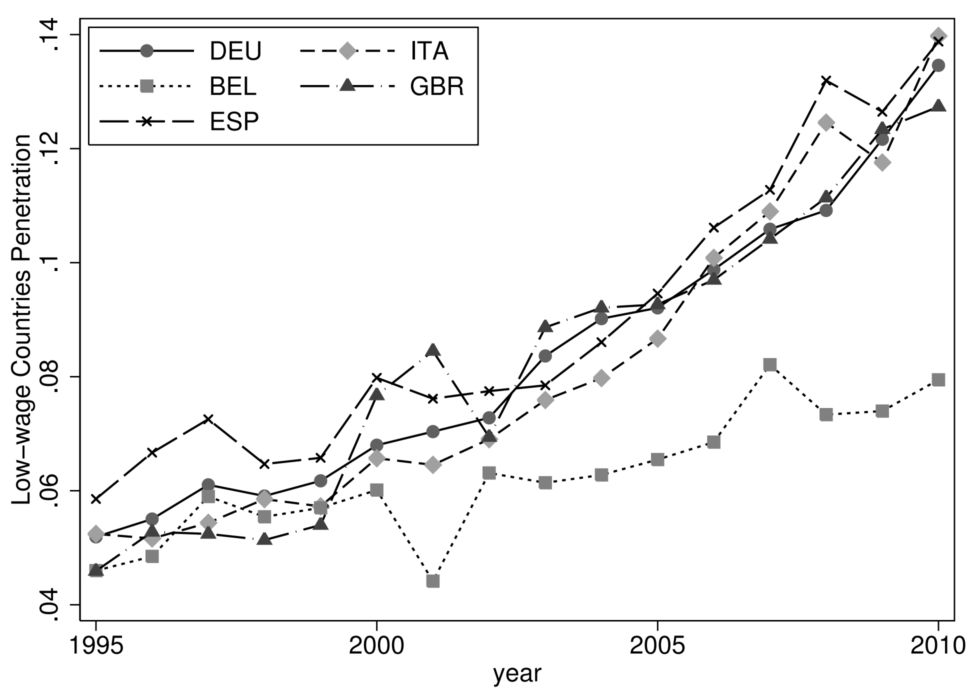
B.8 List of Low-Wage Countries and Import Penetration

Table B.6: Low-Wage Countries

Angola	Djibouti	Lao People's Rep.	Rwanda
Armenia	East Timor	Lesotho	Senegal
Azerbaijan	Eritrea	Liberia	Sierra Leone
Bangladesh	Ethiopia	Madagascar	Solomon Islands
Benin	Gambia	Malawi	Sri Lanka
Bhutan	Georgia	Mali	Sudan
Bolivia	Ghana	Mauritania	Tajikistan
Burkina Faso	Guinea	Moldova, Rep. of	Tanzania, United Rep of
Burundi	GuineaBissau	Mongolia	Togo
Cambodia	Guyana	Mozambique	Turkmenistan
Cameroon	Haiti	Nepal	Uganda
Central African Republic	India	Nicaragua	Ukraine
Chad	Indonesia	Niger	Uzbekistan
China	Iraq	Nigeria	Viet Nam
Comoros	Kenya	Pakistan	Yemen
Congo	Kiribati	Papua New Guinea	Zambia
Ivory Coast	Kyrgyzstan	Philippines	Zimbabwe

Notes: A low-wage country is defined as a country which GDP per Capita in 2002 is inferior to 5% of the French one in 2002.

Figure B.1: Low-wage Countries' Penetration 1995-2010-Top Source Countries



Appendix C

Appendix for Chapter 3

C.1 Optimizing problems

We check in this section that the Second order conditions for the optimal choice of advertising hold. The firm maximizes $Ln_{1j}\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\frac{1}{\sigma} - L\frac{c_a}{\alpha}n_{1j}^{\alpha} - L\frac{c_a}{\beta}n_{2j}^{\beta}$ relatively to n_{1j} and n_{2j}. We obtain the two second derivatives:

$$\text{SOC 1:} \qquad - c_a(\alpha-1)n_1^{\alpha-2} < 0$$

$$\begin{aligned}
\text{SOC 2:} \qquad & \gamma^2 n_1 \frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\frac{1}{\sigma} - c_a(\beta-1)n_2^{\beta-2} < 0 \\
\iff \qquad & \gamma^2\left[\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\frac{1}{c_a\sigma}\right]^{\frac{\alpha}{\alpha-1}} - (\beta-1)n_2^{\beta-2} < 0 \\
\iff \qquad & \gamma n_2^{\beta-1} < (\beta-1)n_2^{\beta-2} \\
\iff \qquad & n_2 < \frac{\beta-1}{\gamma} \\
\Longleftarrow \qquad & \gamma < \beta - 1
\end{aligned}$$

Therefore, the condition $\gamma < \beta - 1$ is sufficient to ensure the concavity at the value of n_2^*. Because this solution is unique and the problem is continuous, this ensures that the solution is a maximum.

C.2 Advertising intensity derivations

Informative case:

$$
\begin{aligned}
A_{1j} &= \frac{\frac{c_a}{\alpha} n_{1j}^{*\alpha} L}{n_{1j}^{*} \frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \left(\frac{1}{\sigma}+c\right) L} \\
&= \frac{\frac{c_a}{\alpha} n_{1j}^{*\alpha-1}}{\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \left(\frac{1}{\sigma}+c\right)} \\
&= \frac{1}{\alpha(1+\sigma c)} \qquad \text{using the FOC:} \quad n_{1j}^{*\alpha-1} = \frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \frac{1}{c_a \sigma}
\end{aligned}
$$

Persuasive case:

$$
\begin{aligned}
A_{2j} &= \frac{\frac{c_a}{\beta} n_{2j}^{*\beta} L}{n_{1j}^{*} \frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \left(\frac{1}{\sigma}+c\right) L} \\
&= \frac{c_a \gamma^{\frac{\beta}{\beta-1}} \left[\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \frac{1}{c_a \sigma}\right]^{\frac{\beta\alpha}{(\alpha-1)(\beta-1)}}}{\beta \left[\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \frac{1}{c_a\sigma}\right]^{\frac{1}{\alpha-1}} \frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \left(\frac{1}{\sigma}+c\right)} \qquad \text{using the definitions of } n_1^* \text{ and } n_2^* \\
&= \frac{c_a}{\beta} \gamma^{\frac{\beta}{\beta-1}} \left[\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)}\right]^{\frac{\alpha}{(\alpha-1)(\beta-1)}} \left(\frac{1}{c_a\sigma}\right)^{\frac{\beta\alpha-\beta+1}{(\alpha-1)(\beta-1)}} \frac{1}{\left(\frac{1}{\sigma}+c\right)} \\
&= \frac{c_a}{\beta} \gamma^{\frac{\beta}{\beta-1}} \left[\left[\frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \frac{1}{c_a\sigma}\right]^{\frac{1}{\alpha-1}} \frac{\exp(q_j+\gamma n_{2j})}{\sum_{s=1}^{J}\exp(\bar{q}_s)} \left(\frac{1}{\sigma}+c\right) L\right]^{\frac{1}{\beta-1}} \left(\frac{1}{L}\right)^{\frac{1}{\beta-1}} \left(\frac{1}{c_a(1+\sigma c)}\right)^{\frac{\beta}{\beta-1}} \\
&= \frac{1}{\beta} \left(\frac{1}{c_a}\right)^{\frac{1}{\beta-1}} \left[\frac{\gamma}{1+\sigma c}\right]^{\frac{\beta}{\beta-1}} \left[\frac{R_j}{L}\right]^{\frac{1}{\beta-1}} \qquad \text{using the formula for } R_j \text{ and } n_1^*
\end{aligned}
$$

C.3 Derivation with a general demand system

In order to not make assumptions on the demand system - and therefore the profit function, we assume that the profit of the firm is $\Pi(n_1, n_2) = n_1 L \pi(q+\gamma n_2) - L\frac{c_a}{\alpha} n_1^{\alpha} - L\frac{c_a}{\beta} n_1^{\beta}$. The only assumption we will make is that $\pi()$ is an increasing and convex function. Moreover, we assume that the revenue of a firms is a proportional function of its profit. Such that $R = m n_1 L \pi(q+\gamma n_2)$

Optimization Given this profit function, the two first order conditions are

$$\begin{aligned} L\pi(q+\gamma n_2) &= c_a L n_1^{\alpha-1} = 0 \\ n_1 L\gamma\pi'(q+\gamma n_2) &= c_a L n_2^{\beta-1} \end{aligned} \tag{C.1}$$

As previously with a specified demand system, we need to prove the unicity of the solution. The first-order condition relative to n_2 can be rewritten $n_2^{\beta-1} c_a^{\frac{\alpha}{\alpha-1}} = \gamma\pi(q+\gamma n_2)^{\frac{1}{\alpha-1}}\pi'(q+\gamma n_2)$. Assuming that $\pi()$ is convex, both of these functions are strictly monotonic in n_2. Moreover, we know that the right-hand side goes from 0 to $c_a^{\frac{\alpha}{\alpha-1}}$ when n_2 goes from 0 to 1. As previously used, a large enough value for c_s ensures us the existence of a solution for n_2: this will indeed ensure that the right-hand side is larger than the left-hand side at $n_2 = 1$. To prove the unicity of the solution, we look at the second derivative at the value of n_2^*. The condition is the following, evaluated at n_2^*

$$\begin{aligned} \frac{\partial^2\Pi(n_1,n_2)}{(\partial n_2)^2} =& n_1 L\gamma^2\pi''(q+\gamma n_2) - c_a(\beta-1)L n_2^{\beta-2} \\ =& n_2\gamma\frac{\pi'(q+\gamma n_2)}{\pi''(q+\gamma n_2)} - (\beta-1) \end{aligned} \tag{C.2}$$

Because we have shown there is at least one solution, we also know that if there is more than one solution, those solutions have to be located on concave and convex sections of the profit function. Moreover, there should be one more solution on a concave area in comparison with a convex area. This implies that we cannot have an unique solution in a convex area, such that this unique solution is a maximum. A sufficient condition is therefore : $n_2\frac{\pi'(q+\gamma n_2)}{\pi''(q+\gamma n_2)}$ is monotonic in n_2. This ensures unicity and concavity at this unique point.

Advertising intensity Given this solution, we can derive the advertising intensity optimally chosen by the firm:

$$
\begin{aligned}
A_1 &= \frac{L\frac{c_a}{\alpha}n_1^\alpha}{n_1 L\pi(q+\gamma n_2)m} = \frac{1}{\alpha m} \\
A_2 &= \frac{L\frac{c_a}{\beta}n_2^\beta}{n_1 L\pi(q+\gamma n_2)m} = \frac{n_2\gamma\pi'(q+\gamma n_2)}{\pi(q+\gamma n_2)m\beta} \\
&\qquad = \frac{\gamma^{\frac{\beta}{\beta-1}}}{m\beta}(\frac{1}{c_a})^{\frac{\alpha}{(\alpha-1)(\beta-1)}}\pi'(q+\gamma n_2)^{\frac{\beta}{\beta-1}}\pi(q+\gamma n_2)^{\frac{\alpha}{(\alpha-1)(\beta-1)}-\frac{\beta}{\beta-1}} \\
&\qquad = \frac{1}{\beta}\left(\frac{1}{c_a}\right)^{\frac{1}{\beta-1}}\left(\frac{\gamma\pi'(q+\gamma n_2)}{m\pi(q+\gamma n_2)}\right)^{\frac{\beta}{\beta-1}}\left(\frac{R}{L}\right)^{\frac{1}{\beta}}
\end{aligned}
\tag{C.3}
$$

We can see that, by setting $m = 1+\sigma c$ and $\pi(q+\gamma n_2) = \pi'(q+\gamma n_2)$, we obtain the results from the initial model. An interesting case is a CES framework for the demand system. In this case, we have $m = \sigma$ and $\pi(q+\gamma n_2) \propto (q+\gamma n_2)^{\sigma-1}$. With this special case, we obtain

$$
\begin{aligned}
A_1 &= \frac{1}{\alpha\sigma} \\
A_2 &= \frac{\gamma^{\frac{\beta}{\beta-1}}}{m\beta}(\frac{1}{c_a})^{\frac{\alpha}{(\alpha-1)(\beta-1)}}\left(\frac{\gamma(\sigma-1)}{\sigma(q+\gamma n_2)}\right)^{\frac{\beta}{\beta-1}}\left(\frac{R}{L}\right)^{\frac{1}{\beta}} \propto (q+\gamma n_2)^{\frac{\sigma-1-\beta}{\beta-1}}
\end{aligned}
\tag{C.4}
$$

The relationship between the advertising intensity and the size of the firm depends on the sign of $\sigma - 1 - \beta$. The intuition is a race between the quality elasticity of the profit function ($\sigma - 1$) and the elasticity of the cost function (β). More importantly, two general results can be emphasized. First a model of informative advertising predicts a constant advertising intensity between firms. This is true for the CES system but also any demand system with constant markup. Secondly, the ability of the firm to vertically differentiate its product (parameter γ) boosts the slope between size and advertising intensity.

C.4 Prediction of Arkolakis (2010)

We start by showing that condition (3.15) never holds for $\delta < 1$. Then we will extend the proof for $\delta \leq 1$. Given the initial function $f(n) = \frac{1-(1-n)^{1-\delta}}{1-\delta}$, we obtain $f'(n) = (1-n)^{-\delta}$ and $f''(n) = \delta(1-n)^{-\delta-1}$. Therefore, the condition (3.15) becomes

$$\frac{n(1-n)^{-\delta}}{\frac{1-(1-n)^{1-\delta}}{1-\delta}} > \frac{n\delta(1-n)^{-\delta-1}}{(1-n)^{-\delta}} + 1 \iff \frac{(1-\delta)(1-n)^{-\delta}}{1-(1-n)^{1-\delta}} > \frac{\delta}{(1-n)} + \frac{1}{n}$$

$$\iff (1-n)^{-\delta} > \frac{\delta}{1-n} + \frac{1}{n} - \frac{(1-n)^{1-\delta}}{n} \text{ if } \delta < 1$$

$$\iff (1-n)^{-\delta}(1+\frac{1-n}{n}) > \frac{\delta}{1-n} + \frac{1}{n}$$

$$\iff (1-n)^{1-\delta} > 1-(1-\delta)n$$

In order to prove that this last condition never holds, we start by noticing that for $n = 0$ both sides of the formula equal one. In order to prove that $(1-n)^{1-\delta} \not> 1-(1-\delta)n$, we will show that the derivative of the left hand side is strictly smaller at each point n. Because the function is derivable for all $n > 0$, and both sides of the equation are equal at $n = 0$, a lower derivative of the left hand side would imply that it never gets larger than the right hand side. The derivative of the LHS is $-(1-\delta)(1-n)^{-\delta}$ and is lower than $-(1-\delta)$ since $(1-n)$ is always smaller than one. Therefore, the left-hand side decreases faster than the right-hand side such that the condition never holds.

In order to prove this for $\delta > 1$, the method is similar except that we obtain the condition $\frac{1}{(1-n)^{\delta-1}} < 1+(\delta-1)n$. Since the derivative of the left hand side is larger than the right hand side, this condition will never hold.

Finally, in the case where $\delta = 0$, the function $f(n)$ is defined as $f(n) = -\log(1-n)$ such that $f'(n) = \frac{1}{1-n}$ and $f''(n) = \frac{1}{(1-n)^2}$. Therefore, condition (3.15) becomes

$$\frac{-1}{(1-n)\log(1-n)} > \frac{1}{1-n} + \frac{1}{n} \iff (1-n)\exp(n) > 1 \tag{C.5}$$

Once again, we follow the same method. We can see that the two sides of the constraint are equal for $n = 0$. Moreover, since the derivative of the right-hand side is $-nexp(n)$ and is strictly negative for $n > 0$, we conclude that the right hand side will be strictly lower than the left hand side on the definition set of n.

Alternatively, the condition derived in the case of persuasive advertising is not as restrictive as the previous one. Indeed, using the functional form from Arkolakis (2010) and following the same method as above, the condition (3.16) becomes:

$$
\begin{aligned}
(1-n)^{1-\delta} &> \delta & &\text{if} \quad \delta < 1 \\
\frac{1}{(1-n)^{\delta-1}} &< \delta & &\text{if} \quad \delta > 1 \\
n &< 1 - \exp(-1) & &\text{if} \quad \delta = 1
\end{aligned}
$$

We therefore can see that there exists a subset of values, for the parameter δ and the variable n, for which this condition holds.